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Energy and Environmental Contexts of Cities, Transportation Systems, and Emerging Vehicle Technologies: How Plug-In Electric Vehicles and Urban Design Influence Energy Consumption and Emissions

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Energy and Environmental Contexts of Cities, Transportation Systems, and Emerging Vehicle Technologies: How Plug-In Electric Vehicles and Urban Design Influence Energy Consumption and Emissions

by

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Preface

This thesis is separated into two distinct parts, focusing first on life-cycle energy analysis of different land-use patterns, and then on the emissions greenhouse gas implications of electric vehicles in Texas. Both parts are share the concepts of transport policy and design, energy use and emissions, and a life-cycle perspective for evaluating urban patterns and policies; but they were researched under distinct research projects. Despite the diverse topics, there is much overlap between vehicle choices and land-use, since so much energy consumption and so many transport-based emissions come via vehicle ownership and use decisions, which are affected by design of our built environments.

To these ends, this study explores several potential futures that North American cities may pursue, in terms of city structure, vehicle choices, and electricity sources. It anticipates the resulting travel, energy, emissions, and public health impacts relative to efforts to promote system-wide efficiency and sustainability.

The first part of this thesis, focusing on the embodied and operational energy implications of different neighborhood and city designs, contains the details of a paper under review for publication in *Energy Policy* and presented at the Transportation Research Board's annual meeting in January, 2014, with Kara Kockelman as co-author. This first topic also describes the life-cycle energy impacts of different cityscapes, and has resulted in a second paper with Kara Kockelman as co-author, as presented at the 60th Annual North American Meetings of the Regional Science Association International and under review for publication in the *Journal of Transportation and Land Use*.

The second part of this thesis, which tackles the emissions implications of plug-in electric vehicle adoption, was part of a research project funded by a collaboration between the National Science Foundation and several industry partners.

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by

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This thesis is divided into two parts. The first evaluates the role of the built environment in life-cycle energy consumption, by comparing different neighborhood and city styles. Through a holistic modeling and accounting framework, this work identifies the largest energy-consuming sectors, among residential and commercial buildings, personal vehicles and transit trips, and supporting infrastructure (roads, sidewalks, parking lots, water pipes, street lighting). Life-cycle energy calculations include operational energy use (e.g., gasoline for vehicles, electricity and natural gas for buildings) and embodied energy used to produce materials and construct buildings and infrastructure. Case study neighborhoods in Austin, Texas, and larger-scale regional models suggest that building energy demands comprise around 50% of life-cycle energy demands, while transportation demands (from driving and infrastructure alike) contribute around 40%, across all cases. However, results also suggest that population density and average residential unit size play a major role in defining per-capita energy consumption. Operational demands made up about 90% of life-cycle energy demands, suggesting that

most urban energy savings can be obtained from reduced personal vehicle trips and more efficient vehicles and buildings. Case study comparisons suggest that neighborhoods and regions with greater density and higher share of multi-family housing units tend to reduce operational (and thus life-cycle) energy demands with less travel demand and decreased home and work energy use, per capita.

The second part of this modeled plug-in electric vehicle (PEV) emissions impacts in Texas, by considering four possible vehicle adoption scenarios (where PEVs make up 1, 5, 10, and 25% of total passenger vehicles). The analysis anticipates PEV electricity demand and emissions rates, based on current Texas power grid data. Results indicate that PEV emissions depend significantly on which specific power plants are used to power the vehicles, but that PEVs' average per-mile emissions rates for NO_x, PM, and CO_2 are all likely to be lower than today's average passenger car, when today's average mix is used in Texas. Power produced from 100% coal plants could produce 14 times as much NO_x, 3,200 times as much SO_2, nearly 10 times as much CO_2 and CO_2eq, 2.5 times as much PM_{10} and VOCs, and nearly 80 times the NO_2compared to a grid with 100% natural gas plants.

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PART I. LIFE–CYCLE ENERGY ANALYSIS OF BUILDINGS, INFRASTRUCTURE, AND TRANSPORTATION SYSTEMS

CHAPTER 1 : BACKGROUND

Cities are facing unprecedented growth from rising population, migration, and urbanization. The United Nations (2011) anticipates global population will rise to 9.3 billion in 2050, a nearly 30% increase of 2.3 billion from 2013. Meanwhile, urban areas are projected to grow by 2.6 billion, implying a rise in urban population shares from 50 to around 70%. These new residents, workers, and consumers will require more living and working spaces, and supporting infrastructure. Meeting those needs in a sustainable and energy-efficient way is a major design and policy challenge. While much research has considered specific aspects of how city form influences energy use and emissions via travel choices and building energy use, little work aggregates the analysis to a larger city or regional scale. For instance, Cervero and Kockelman (1998) quantify how several built environment features influence vehicle demand, but such findings have rarely been scaled up to consider how different urban forms compare in terms of total energy use as a function of these design variables. Newman and Kenworthy (1989) tallied total gasoline consumption of several different cities across the world, concluding that population and jobs density and transit provision likely do have a large impact on gasoline consumption and automobile dependence.

For the most part, studies of built environments' influence on of vehicle-miles, building energy, and downstream emissions have been at a micro level, and have included only one or two measures of land use patterns. The result is a piecemeal image of how energy consumption varies across specific settings, with little perspective on the "big picture," or how urban planning influences energy at a city level, and whether any of that really matters, at a larger scale. For instance, in a meta-analysis of travel choices vis-a-vis built environment variables, Ewing and Cervero (2010) suggest that vehicle miles traveled (VMT) has an average elasticity of around -0.09 with respect to land use diversity (indicating that a doubling in land use diversity tends to be associated with a nine percent reduction in average VMT). While useful, it is not clear how a nine percent reduction in driving really impacts a region's overall terms of relative energy use. When accommodating thousands and millions of new people, it is unclear whether or not land-use diversity will impact urban energy demand to the same degree as other factors like building design or vehicle technology, for instance.

Research indicates how focusing on all day-to-day energy demands ignores an important source of energy use: the *embodied energy* used to construct, fabricate, ship, maintain, and eventually demolish and dispose of vehicles, buildings, and infrastructure. Together, the day-to-day (operational) and embodied phases of specific materials or structures has been rather heavily researched (though much uncertainty surrounds the analyses) within the field of life-cycle analysis (LCA). LCA provides an appropriately holistic perspective on total energy (or emissions) associated with many of the urban environment's "building blocks," but very few studies have attempted to aggregate micro-scaled LCAs to a neighborhood or regional level. Most studies focus on tracing energy pathways for distinct materials (e.g, Hammond and Jones 2008), single structures like single-family homes (e.g., Keolian et al. 2001), or various types of commercial buildings (e.g., Junnila and Horvath 2006, Fay et al. 2000). However, a study by Norman et al.

(2006) did provide one of the first neighborhood-level LCA perspectives by comparing low- and high-density neighborhoods in Toronto. Their work defined energy sources by sector and phase for the different neighborhoods and identified distinct energy demands across the neighborhoods.

This study expands on Norman et al.'s (2006) work by introducing a more flexible LCA model and expanding domain to an entire urban region. By quantifying holistic energy demands for residents and workers in different urban settings, this work identifies how density patterns influence aggregate emissions rates. The analysis incorporates "building blocks" from different disciplines (travel demand, building design, infrastructure energy and LCA) to construct larger neighborhoods, and finally city patterns. By tiling together different neighborhoods with very different built environments, one can mimic the form of actual U.S. cities. Energy use estimates, by source and phase, are evaluated and compared to infer the impact of the built environment on large-scale energy demands.

While much research has considered built environment (BE) impacts on travel choices, much less research has considered impacts on buildings and infrastructure, even though buildings consume nearly 2.5 times the energy used for U.S. personal transport. Furthermore, the embodied energy of materials for constructing and maintaining buildings and other infrastructure is rarely considered alongside purported transportation energy savings from different BE designs. Thus, a more holistic energy analysis is typically overlooked, and various sectors of the urban environment (e.g., vehicles and roads, residential and commercial buildings) are too rarely compared to identify the most effective "levers" for reducing energy consumption. This analysis emphasizes a more holistic evaluation of BE variations, to better evaluate relative energy savings sources and recommend optimal focus areas.

1.1 URBAN FORM AND ENERGY CONSUMPTION

Perhaps the largest volume of BE analysis considers various impacts to household travel choices. While some conclude that compact, accessible, mixed-use designs reduce driving, and promote transit use and non-motorized travel (NMT) (e.g., Handy 1996a, Levine 1999, Bernick and Cervero 1997, Cervero and Kockelman 1997, Cervero et al. 2002, Khan et.al, 2013), others find relationships to be weak and indirect (Giuliano 1995, Krizek 2003). There is also the issue of self-selection bias (Mokhtarian and Cao 2008), which diminishes most estimates of causation (by perhaps 50 percent [Zhou and Kockelman 2008]). Smart growth practices and related built environment (BE) designs are often advertised as reducing municipal services and infrastructure costs (see, e.g., Burchell et al. 1998, Litman 2013), along with regional congestion, emissions, crashes, and various other transportation-related costs; but these impacts are rarely considered holistically, from an energy and GHG emissions perspective.

Some research efforts extend their analyses to consider impacts of urban systems through microsimulation approaches (see, e.g. Waddell et al. 2003, Maoh et al. 2005, Tirumalachetty et al. 2013, and others), but these often focus on anticipating land-use changes over time, rather than comparing energy use across BE settings. Norman et al. (2006) performed a comprehensive analysis of energy use in two distinct Toronto neighborhoods. In addition to evaluating daily transportation and household energy consumption between low- and high-density neighborhoods, they considered the impacts of embodied energy (i.e., that associated with materials manufacture, construction, and building and infrastructure maintenance). Their life-cycle approach provided a holistic evaluation of all energy sinks across the two neighborhoods, and showed how the low-density neighborhood could be 2 to 2.5 times more energy-intensive (per capita) than the high-density neighborhood, with the embodied energy of neighborhood materials accounting for around 10% of the life-cycle energy use, transportation accounting for 20 to 30%, and building operations from 60 to 70%. Little, if any, other work provides their level of detail and scale. Importantly, their results suggest that the embodied energy and buildings consume a significant portion of a neighborhood's energy use, and should be granted more consideration in land use-transportation analyses.

CHAPTER 2 : METHODS

Though Norman et al. (2006) performed a rigorous life-cycle analysis (LCA), their transportation and buildings energy estimates were taken from aggregate (national) estimates and no heterogeneity across households was considered, resulting in a rigid accounting framework, rather than the more flexible method pursued here, which illuminates impacts of policies changing various BE variables. The model developed here allows one to better understand how land-use policies can affect energy use across different neighborhood types. This approach evaluates the life-cycle energy demands of existing and theoretical neighborhoods in Austin, Texas, in a way that explicitly identifies key levers for urban energy reduction. For instance, how much total energy can be saved by increasing a given neighborhood density, and in which sectors (transportation, buildings, infrastructure) will those impacts be most critical?

This approach requires a system of regression equations and rigorous geographical information system (GIS) analysis to estimate building materials quantities across the distinct neighborhoods (in order to derive embodied-energy estimates). The following sections detail the energy equation development processes pursued to quantify the life-cycle energy demands of five Austin neighborhoods, and then evaluate the elasticity of (expected) energy demands with respect to various BE attributes of each location.

Energy use at a neighborhood scale involves many different subsystems, including buildings (homes, apartments, offices and commercial structures), roadways, sidewalks, driveways, parking structures, water and wastewater systems, municipal lighting, and more (such as natural gas pipes and electric utility infrastructure). These subsystems' key energy requirements are estimated here via models using U.S. data sets, such as the National Household Travel Survey (NHTS) and the Residential and Commercial Building

Energy Consumption Surveys (RECS and CBECS). Other sources, for the materials volumes of streets, sidewalks, and piped systems, for example, were estimated using GIS data from the City of Austin, coupled with satellite imagery and local codes and design standards. Table 2.1 summarizes the various data sources and modeling approaches used (with ordinary least squares [OLS] used for continuous response quantites, and Poisson, negative binomial, and multinomial logit [MNL] specifications used for various discrete response types). Estimated energy requirements are separated by sector (buildings, transportation, and other infrastructure) and by use phase (operational/on-going or embodied/initial construction). Many of these regression models, and the sector divisions, are described in following subsections.

Table 2.1: Models and Data Sources

Sector	Consumption Source(s)	Operational Energy	Embodied Energy	Model(s)/Method	Data Source(s)
Buildings	Electricity	✓		OLS	RECS & CBECS
Buildings	Natural Gas Use	✓		OLS	RECS & CBECS
Buildings	Building Materials		✓	GIS	City of Austin
Transportation	Personal Vehicles' Fuel Use	✓		OLS, Poisson, MNL	NHTS
Transportation	Transit Fuel Use	✓		OLS	Austin Travel Survey
Transportation	Streets		✓	GIS	City of Austin
Transportation	Sidewalks		✓	GIS	City of Austin
Infrastructure	Water & Wastewater		✓	GIS	City of Austin
Infrastructure	Water & Wastewater	✓		GIS	City of Austin
Infrastructure	Street Lighting	✓		GIS	Google Earth

2.1 Case Study Neighborhoods in Austin, Texas

Five distinct neighborhoods were selected to represent a range of densities and building types in residential and commercial neighborhoods. All come from the Austin, Texas area, in order to provide some focus and comparability, but they are general enough to have come from most U.S. urban areas. This analysis separates these five neighborhoods into five residential and three commercial component cells. (Only three commercial cells are considered because commercial and office land uses are nearly nonexistent in two neighborhoods considered.) In this construct, resident energy is measured per capita while commercial energy is measured per worker. To appropriately allocate shares of energy vested in the built environment, embodied energy is allocated to residential (*r*) and commercial (*c*) sources for a neighborhood *i* as follows:

$$EE_{r,i} = x_{r,i} \times EE_{tot,i}$$

where $EE_{r,i}$ is embodied energy allocated to residential components, $EE_{tot,,i}$ is total embodied energy neighborhood i, and $x_{r,i}$ is the share of total floor area (base footprint plus estimated floor areas) used for residences.[1] Embodied energy allocated to employment ($EE_{c,i}$) is the remaining share, calculated as unity less $EE_{r,i}$. Such allocation allows more representative distribution of embodied energy shares from streets, sidewalks, water and wastewater pipes, parking garages, and surface parking facilities to separate residential and commercial uses. Without such a weight, neighborhoods with infrastructure supporting majority commercial purposes would incorrectly appear rather inefficient on a per-capita basis. Operations energy from commercial and office electricity and natural gas use is assigned exclusively on an energy/year/employee basis, and lighting and water use is segmented by residential or commercial use.

As detailed in Table 2.2, the case study neighborhoods range from a proto-typical U.S. suburban subdivision, with curvilinear roads and cul-de-sacs (Anderson Mill [neighborhood #2]), to a very dense, low-rise multi-family apartment area (Riverside [#4]). Hyde Park (#3) offers a rather high density mix of single-family and multi-family

[1] Total building areas are calculated for residential, commercial, and office uses only. Other buildings (e.g., parking garages, government buildings, schools, industrial) are not considered in this split.

homes, on a gridded street pattern, very near Austin's central business district (CBD). The Westlake neighborhood (#1) represents a sprawling, wealthy neighborhood, with semi-rural character mixed in. It varies significantly from Anderson Mill (#2), in its large lots and home sizes, but greater proximity to the CBD. The downtown residential area (#5) is characterized by high-rise condominiums and high-density apartment complex, with a scattering of a few older homes and duplexes. Table 2 characterizes these five neighborhoods while also reporting several model outputs. Neighborhoods are numbered from 1 to 5, based on population density, beginning with the least dense. Each neighborhood's geographical size reflects a census tract, or a combination of two census tracts in the case of 4R – Riverside, to include relatively similar populations, ranging from around 3,300 to 7,700 total residents. The Riverside neighborhood consists of two census tracts to ensure an equal overlap with Austin travel analysis zone (TAZ) data, which was used to derive employment data.

Table 2.2: Residential Neighborhood Characteristics and Summary Statistics (from GIS Analysis and Model Applications)

		1R – Westlake	2R – Anderson Mill	3R – Hyde Park	4R – Riverside	5R – CBD
		Large-lot SFH	Newer, small SFH	Mixed SFH, MFH	Low-rise MFH	Residential, commercial/office towers
Site Attributes & Behavioral Estimates						
Total Population (Census 2010)		4,865	3,394	4,939	7,728	5,512
Total Employment		2,478	313	1,019	763	86,892
Total Area (mi^2)		5.06	0.64	0.86	0.50	1.13
Population Density (residents/mi^2)		962	6,148	5,713	17,249	4,857
Employment Density (employees/mi^2)		490	487	1,179	1,520	76,581
% Detached SFH		93%	92%	65%	8%	6%
% Bldg. Area Commercial/Office		0.0%	2.6%	18.6%	14.3%	80.5%
Miles from Centroid to Austin CBD		4.5	13.4	2.5	2.3	0
Streets (centerline miles/capita)		13.59	15.43	12.10	3.30	1.48
(Directional) Sidewalks (miles/capita)		2.83	22.62	7.49	2.97	1.8
Transit Stops per mi^2		0	0	27	18	75
Water & Wastewater Pipes (mi/capita)		14.16	11.76	12.64	3.88	1.06
Avg. LDV VMT/HH/year		8,200	7,984	7,077	7,096	1,380
Behavioral Estimates/Outputs						
Avg. Vehicles per HH		1.69	1.68	1.27	1.04	1.43
Vehicle -Type Shares	Passenger Car	64%	63%	68%	68%	64%
	Van	12%	12%	11%	12%	11%
	SUV & CUV	18%	19%	17%	17%	17%
	Pickup Truck	6%	6%	3%	4%	7%
Avg. LDV Fuel Economy (mi/gal)		23.2	23.3	23.5	23.7	23.6
Avg. LDV Fuel Use (gal/year/HH)		849	832	584	473	260
Annual HH Transit Miles		944	470	398	760	136
Avg. HH NG Use(GJ/year)		97.9	91.6	74.9	66.9	73.6
Avg. HH Electricity Use (GJ/year)		26.9	24.8	21.8	22.0	21.8

Note: SFH and MFH stand for single- and multi-family housing, LDV is for light-duty vehicle (cars and trucks), HH signifies household, and NG is natural gas. Miles from centroid is the Euclidean distance from centroid to downtown Austin, set at the intersection of 6th St. and Congress Ave.

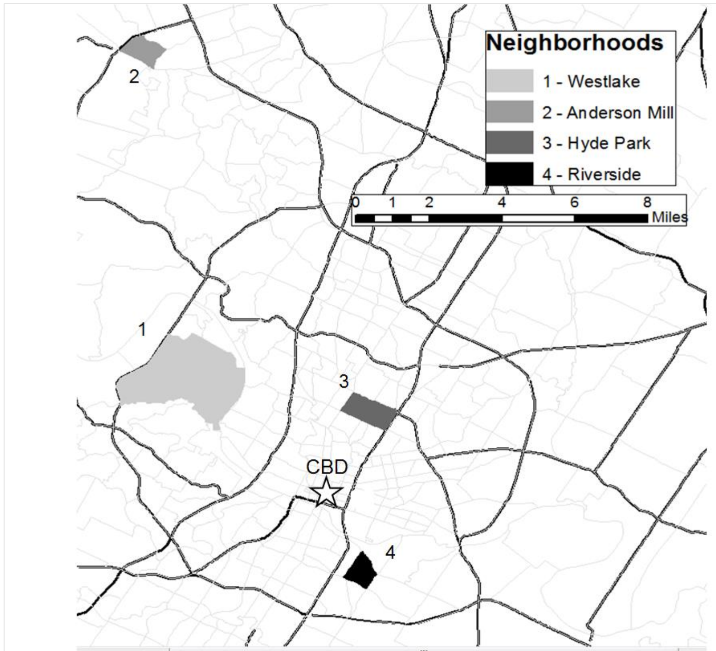

Figure 2.1: Map of Selected Austin, Texas Neighborhoods

Table 2.2's summary and Figure 2.1 illuminate these residential neighborhoods' clear diversity, even within a single urban area. The settings vary dramatically, and some land-use patterns clearly demand greater travel, infrastructure provision, and energy expenditure. For instance, the number of street centerline-miles per capita is much higher for the mostly-SFH neighborhoods, especially in suburban neighborhoods 1 and 2. Water and wastewater pipe infrastructure demands (per capita) are also much greater for the lower-density developments (neighborhoods R1-WL and R2-AM).

2.2 Population Synthesis

To ensure comparability in energy expenditures, the same cross-section of residential population was assumed in all neighborhoods. In this way, one controls for demographic variation and is able to evaluate energy differences based solely on each neighborhood's BE and regional location characteristics. Thirty-nine different household types were considered, and distributed based on the Austin-Round Rock-San Marcos metropolitan statistical area (MSA) demographics in 2010, based on household size (1 to 4+ persons), number of workers (0 to 3+ per household), and (annual) income level (low [<$15,000 per household per year], medium [$15,000 – $50,000] and high [>$50,000]). Using a Public Use Microdata Sample seed for the MSA and marginal distributions on each of the 3 attributes, household shares were distributed across the 39 classes using an iterative proportional fitting procedure (see, e.g., Feinberg [1970] and Norman [1999]).

For instance, results indicate that only about 2% of the area households have a combination of 4-or-more members, 3-or-more workers, and a medium income level, while 10% of area households are classified as having only one member, who is employed, and at the low-income stratification. This approach provides an approximation of the Austin area population with sufficient resolution to allow for variation within the various models, without creating an unwieldy cross-section sample. Appendix A shows distribution of the regional population across different household types.

While the mix or shares of household types is constant across the distinctive neighborhoods studied, neighborhood population and number of dwelling units vary, so all results are normalized by population (which is extracted from Census of Population 2010 data). All dwelling units are considered 100% filled, which may be unrealistic, but represents the best case scenario when considering per-capita impacts. Additionally, average vacancy rates for rented and owned units are considerably different,[2] potentially skewing a pure energy and BE analysis.

2.3 Operational Energy Models

In this model, operational (i.e., day-to-day) energy use includes residential and commercial electricity, natural gas, water, and wastewater consumption, fuel use from personal (household-owned) light-duty vehicles (LDVs), and public street lighting. When possible, these values were estimated via behavioral models (using regression equations for vehicle ownership details, driving distances, transit use, and building energy use [per SF of building interior]), but the energy-related water and wastewater estimates rely on aggregate assumptions (from Austin, California, and Florida studies) and GIS-based tabulations (of actual infrastructure observed in the neighborhoods).[3]

2.3.1 Transportation Operational Energy

Transportation energy use was estimated for LDVs and transit via fuel-use models, composed of several sub-models. This approach does not employ detailed networks and regional (zone-based) travel demand models, but rather relies on household demographics and BE characteristics to estimate the number and types of vehicles owned by each household, the number of vehicle miles traveled (VMT), and owned-vehicle fuel economies, to predict each household's annual fuel use in driving, along with the annual

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[2] In the first quarter of 2013, average U.S. rental-housing vacancy rates (typically associated with multi-family units) were 8.6% while the average vacancy rate of individually owned homes (typically single-family units) was 2.1% (Census 2013).

[3] These categories represent the largest sources of urban energy use, both publically and privately, though other energy sources could certainly be included. For instance, life-cycle impacts of urban waste collection services have previously been evaluated (Iriarte et al. 2008), but are excluded in this analysis, due to data scarcity.

number of transit trips and (average) transit trip lengths. Focusing on just personal vehicles and transit energy uses, however, does capture a large share of total energy use. Personal vehicles alone consume 60% of all transportation energy (which in turn consumes about 28% of all U.S. energy) and trains and buses consume an additional 3% of transport demands (NAS 2013). Air travel consumes 9% (of transport energy), and other sources (mostly trucks) consume the remaining 30%. This study captures nearly all energy directly consumed by household travels, and the rest (freight and industrial uses) is outside the influence of urban design and policy. Altogether, the household travel energy calculated here does comprise a large share of national energy use (around 63%) and is thus an important set of sources to consider.

All the LDV sub-models were estimated using the nation's 2009 NHTS data. The number of household vehicles owned (by vehicle type: passenger car, van, SUV, and pickup truck) was estimated using Poisson regression, to reflect the integer (or "count") nature of this variable, as shown in Table 2.3. (A negative binomial model was originally specified, but a statistically insignificant dispersion parameter effectively collapsed the model to a Poisson specification.)

Table 2.3: Poisson Model for Household Vehicle Counts

Parameter	Beta (Std. Error)	Wald Chi-
(Intercept)	-0.401 (0.017)	570.1
Household Income	0.023 (0.000)	3310
Household Size	0.013 (0.002)	42.32
Home Owner Indicator	0.233 (0.008)	908.9
Single Family Home Indicator	0.115 (0.006)	393.6
MSA Size (as per NHTS 2009)	0.003 (0.001)	5.511
Heavy Rail in MSA Indicator	0.032 (0.006)	31.29
Urban Area Indicator	-0.104 (0.005)	522.1
Household Worker Count	0.075 (0.003)	932.7
Residential Density (per mi^2, at Census Tract Level)	-2.624E-005 (0.000)	212.1
Population Density (per mi^2, at Census Tract Level)	-6.634E-007 (0.000)	0.454
Employment Density (per mi^2, at Census Tract Level)	-1.431E-005 (0.000)	53.18
Number of Adults per Household	0.247 (0.004)	5,043
Number of Observations	137,591	
Log Likelihood	-197513	

Note: MSA (metropolitan statistical area) size and urban area designations are defined by NHTS (2009).

Household vehicle type choice was modeled using a multinomial logit (MNL) specification, generating probabilities or shares of each of the four vehicle types for each household, as shown in Table 2.4. These probabilities were multiplied by the estimated vehicle holdings to produce the weighted average number of each vehicle owned, by household. (It may seem strange that a household is assumed to own 1.45 SUVs and 0.90 cars, for instance, but this represents the average split of vehicles across a number of households with similar demographic and locational attributes.)

Table 2.4: MNL Specification for Household Vehicle Counts by Type (Base Choice is Passenger Car)

	Van (Std. Error)	SUV (Std. Error)	Truck (Std. Error)
Intercept	-0.603 (0.186)	-0.608 (0.128)	-1.604 (0.130)
Household Income	-0.016 (0.002)	0.051 (0.001)	-0.021 (0.001)
Household Size	0.512 (0.007)	0.207 (0.006)	0.067 (0.006)
Number of Vehicles per Household	-0.073 (0.008)	-0.033(0.005)	0.169 (0.004)
Number of Adults in Household	-0.312 (0.014)	-0.211(0.011)	-0.111 (0.011)
MSA Size (as per NHTS 2009)	-0.012 (0.005)	0.017 (0.003)	0.046 (0.003)
Urban Area Indicator	-0.08 (0.019)	-0.196 (0.013)	-0.502 (0.013)
Home Owner Indicator	0.282 (0.031)	0.123 (0.023)	0.268 (0.024)
Annual VMT (1000 miles/year)	0.008 (0.001)	0.010 (0.041)	-0.002 (0.041)
Gas Cost ($/gallon)	-0.607(0.059)	-0.408 (0.041)	0.141 (0.017)
Single Family Home Indicator	0.22 (0.024)	0.164 (0.017)	-0.539 (0.019)
Heavy Rail in MSA Indicator	-0.029 (0.224)	-0.115 (0.016)	0.185 (0.017
Household Worker Count	-0.103 (0.010)	0.031 (0.007)	0.046 (0.007)
Tract Res. Density (1000 dwelling units/mi^2)	-0.021 (0.008)	-0.007 (0.005)	-0.106 (0.009)
Tract Pop. Density (1000 persons/mi^2)	0.003 (0.004)	0.002 (0.003)	0.013 (0.004)
Tract Employment Density (1000 jobs/mi^2)	-0.019 (0.008)	-0.031 (0.005)	-0.074 (0.001)
Number of Observations (130,359 for base passenger car)	21,079	51,955	52,783
Pseudo R-Square (McFadden)	0.39		

U.S. EPA-rated fuel economy was provided in the NHTS for each vehicle (by make, model, and production year) and these values were then estimated using OLS regression, with indicator variables for three of the four vehicle types, as specified in Table 2.5. Household-level VMT was also estimated using OLS (while controlling for household, neighborhood, and vehicle attributes [including fuel economy, gas cost, vehicle age and type]), with all results fed into a final OLS model for each household's annual fuel use, shown in Table 2.6. Separating the fuel use model into multiple components allowed separate estimates for number of vehicles by type, which allowed embodied energy calculations by vehicle type.

Table 2.5: OLS Specification for Vehicle Fuel Economy (miles/gallon)

Parameter	Beta (t-stat)
Constant	25.27 (91.79)
Household Driver Count	0.230 (9.00)
Household Income	-0.042 (-15.24)
Household Size	-0.07 (-5.16)
Household Vehicle Count	-0.247 (-20.82)
Urban Area Indicator	-0.057 (-1.98)
Household Worker Count	0.355 (21.84)
Vehicle Age	-0.227 (121.46)
Home Owner Indicator	-0.241 (-4.66)
Single-Family Home Indicator	-0.239 (-6.37)
Number of Observations	202,711
Adjusted R^2	0.587

Table 2.6: OLS Specification for Vehicle Fuel Use (gallons/year)

Parameter	Beta
Constant	595.52
Household Size	14.28
Household Vehicle Count	7.611
Number of Adults in Household	-20.58
Heavy Rail in MSA Indicator	-9.296
Household Worker Count	10.77
Vehicle Age	-0.53
Home Owner Indicator	-7.544
% Renter Occupied Units in Tract	0.187
Fuel Economy (miles/gallon)	-12.28
Gas Cost ($/gallon)	-34.28
Annual Miles	0.031
Van Indicator	39.26
Truck Indicator	79.68
SUV Indicator	75.51

Transit trips were modeled using the 2005/2006 Austin Travel Survey data, which is similar to the NHTS data set, but provides additional information on individuals' (monthly) transit use frequency and average trip length. Two (log-transformed) OLS models were estimated with the NHTS data: for number of transit trips per person and transit trip distances, as shown in Tables 2.7 and 2.8, respectively.

Table 2.7: OLS Model for ln(Monthly Transit Trips per Person)

Parameter	Beta (t-stat)
Constant	1.46 (34.17)
Household Income	-0.002 (-2.075)
Household Size	0.01 (1.387)
Household Vehicle Count	-0.162 (-20.22)
Number of Adults	0.126 (9.283)
Worker Count	0.051 (4.006)
MSA Size	0.022 (3.401)
Residential Density (per mi^2)	2.604 E-5 (10.19)
Population Density (per mi^2)	9.267 E-6 (4.487)
Employment Density (per mi^2)	4.500 E-6 (0.764)
Distance to Work (miles)	0.005 (11.10)
SFH Indicator	-0.113 (-5.316)
Urban Location Indicator	-0.185 (-8.497)
Rail Indicator	-0.036 (-1.944)
Worker Indicator	0.188 (8.780)
Home Owner Indicator	-0.123 (-5.454)
Number of Observations	27,016
R^2	0.097

Table 2.8: OLS Model for ln(Transit Trip Length)

Parameter	Beta (t-stat)
Constant	1.646 (8.746)
Worker Indicator	-0.396 (-3.146)
Income	0.025 (1.443)
Stops per Mile	-0.012 (-3.152)
SFH Indicator	0.233 (1.831)
LN(Employment Density)	-0.156 (-3.033)
Number of Observations	27,016
R^2	0.588

Trips per person were estimated for workers and non-workers and trip lengths were specific for each person in a household. Model predictions were scaled to the neighborhood zone level by multiplying the 39 individual results (for each neighborhood) by household size, and then household count, while reflecting the share of employed workers. Total annual energy from transit passenger miles ($E_{tr,i}$) was computed for each household i as follows:

$$E_{tr,i} = \frac{\eta}{occ} \times d_{tr,i}$$

where η is average transit vehicle efficiency (in megajoules [MJ] per vehicle-mile), *occ* is average bus occupancy, and $d_{tr,i}$ is total transit passenger miles traveled per household i. Here, transit vehicle efficiency is assumed to be 37.9 MJ/vehicle-mile, using an average city bus in 2010 (U.S. DOE 2012), and average bus occupancy of 10 persons, based on the most recent data available from Austin's transit provider (CapMetro 2013). Bus occupancy is important for determining efficiency of passenger miles traveled, and varies across cities, and across different routes in the same city. Though occupancy may increase in urban environments, overall efficiency may be reduced with increased congestion (Kockelman et al. 2008).

2.3.2 Residential and Commercial Buildings Operational Energy

Daily energy use in U.S. residential and commercial buildings included electricity and natural gas consumption, as modeled by Tirumalachetty et al. (2013) using data from the 2001 Residential Energy Consumption Survey (RECS) and 2003 Commercial Building Energy Consumption Survey (CBECS). Tirumalachetty et al. (2013) controlled for a number of climatic, demographic, and BE explanatory variables, and used such models for an integrated transportation-land use-GHG microsimulation of the Austin region (but without as much attention paid to BE impacts and no consideration of embodied-energy impacts). Their residential energy-use models were estimated for each of the 39 household types modeled here, using the average number of children and elderly (over age 65) for the Austin-Round Rock-San Marcos MSA (Census 2010). Building-specific variables included home age, square footage, and indicators for urban versus suburban location, and single-family versus multi-family unit type. Electricity and natural gas costs (per kWh and MMBtu, respectively) were also controlled for, and relied on state average residential rates of $0.09/kWh for electricity (EIA 2012) and $10.90/MMBtu for natural gas (EIA 2013).

2.3.3 Utilities Operational Energy

Street lighting, water, and wastewater require energy as well. Street lights constitute a costly portion of a municipality's expenses (The Atlantic 2012), and these were noted across the four Austin neighborhoods using Google Earth satellite and Street View imagery. Each lamp was assumed to have the standard 250-watt high-pressure sodium bulb (City of Austin 2011) and operate from sunset to sunrise, or 12 hours per day, using about 3 kWh per fixture per day.

Household and commercial water use requires significant energy, for treatment and distribution (such as chlorination and pumping). Some of the consumed water is removed from the buildings and processed at a wastewater treatment plant, which requires further energy input. Detailed residential and commercial water use data are rarely collected, so aggregate estimates were assumed here. Each household was assumed to use 275 gallons of fresh water per day per household, based on City of Austin estimates (Fodor 2011). Average commercial building water use was assumed to be 0.142 gallons/ft^2/day, according to studies of Florida cities (Morales and Heaney 2010). Wastewater use (for residential and commercial buildings) was assumed at 40% of freshwater use, to include only drain flows of indoor uses (e.g., dishwasher, bath, faucet, shower, and toilet) (Mayer et al. 1999). The energy costs of water treatment, distribution, and wastewater treatment were assumed to be 1,200, 2,500, and 1,400 kWh per million-gallons, respectively, based on averages from several California systems (Klein et al. 2005). It would be desirable to separate these uses and estimate a model for each household, since water use (and associated energy demands) presumably varies across household demographics and settings, including as a function of various BE factors (Wentz and Gober 2007) and pumping distances. However, early results indicated that water-related energy use was a relatively insignificant energy draw, so such efforts are expected to be insignificant at the neighborhood scale, relative to other sources.

2.4 EMBODIED ENERGY

To estimate embodied energy impacts of urban design, this work emphasizes land uses and building types and applies a range of typical embodied-energy values per unit area (for buildings) or volume (in the case of roads and sidewalks). A more sophisticated evaluation of embodied energy may estimate volumes of all materials used in buildings (and their cost inputs) and perform a detailed economic input-output analysis (as performed by Norman et al. [2006] and developed by Hendrickson et al. [1998]) or follow a process-based analysis that traces all materials back to their manufacturing source (see, e.g., Rebitzer et al. 2004). Such approaches, however, require much time and access to data, beyond the scope of this multi-facility, whole-neighborhood investigation. Moreover, they are probably too finely detailed to provide any tangible accuracy benefits, when considering that all neighborhood structures and estimation approaches used (here, and in the competing input-output life-cycle analyses) are highly variable. This work builds off existing research and compiles results from a number of fields to estimate total embodied energy for complex urban systems and building mixes.

Building, vehicles', and materials' lifespans are a key assumption for embodied energy analysis. Here, all energy demands are annualized, and longer life-span assumptions reduce the relative impact of the embodied energy phase. When possible, well-documented lifespans were selected (as described in Appendix A) and kept constant across neighborhoods for consistency. However, such numbers can vary, changing the relative roles of different neighborhood features. The following sections describe point estimates selected based on literature surveys, but sensitivity analyses are later performed to better capture potentially large variability in embodied and operational energy, as well as building and infrastructure life spans.

2.4.1 Infrastructure Embodied Energy

Streets, roads, driveways, and parking lots, cover a large share of a city's surface, requiring much concrete, asphalt, and base materials for construction and maintenance. Chester (2010) estimates there to be between 100 million to 1.1 billion parking spaces in the United States, consuming around 30 to 475 million ft^2 of land area. Therefore, parking and roadways combined make up around 0.5 to 0.9% of total U.S. surface area (Chester 2010), and likely much larger shares in urbanized areas.

Street characteristics vary by their functional classification in terms of width, paving material, depth, curb and gutter, lane marking, and signage. This analysis considered neighborhoods with a range of roadway types, but mostly involved local streets and minor arterials (though some neighborhoods included sections of major arterials and highways). City of Austin GIS files provided road centerlines and classifications, and road widths were assumed to follow existing City design standards, by classification. By inspection, all roads were assumed to be asphalt topped, with depths based on anticipated average daily traffic (for each class) using AASHTO (1998) guidelines, and an optimistic lifespan of 20 years.[4]

Sidewalk material volumes were estimated similarly for each neighborhood, using Austin GIS centerlines, and city design standards for materials, depth, and width (City of Austin 2013). Sidewalk data files also included information on driveway entrances crossing sidewalks, which was used to extrapolate total driveway volumes, assuming an average depth and length for each neighborhood. Sidewalks were assumed to have a

[4] Chester et al. (2010) used an asphalt lifespan of 10 years for parking surfaces.

lifespan of 35 years (City of Dover 2006) and driveways a lifespan of 20 years (Seiders et al. 2007) Such assumptions are probably most accurate for newer neighborhoods with more uniform designs; older Austin neighborhoods tended to have highly variable driveway lengths and materials (based on visual inspection from satellite imagery, Google's StreetView, and site visits), ranging from concrete to dirt and rock, or brick, so some modifications are also considered.

In addition to streets and sidewalks, parking lots and garages consume a great deal of land (Chester et al. 2010). Parking infrastructure energy was estimated from City of Austin land-use GIS data. Parking structure floor area was estimated from building footprint data, multiplied by the number of floors for each structure (through visual inspection). An embodied energy range of 79 to 215 MJ/ft^2 (depending on construction materials and technique) was applied to total floor space, based on detailed life-cycle analyses from Griffin et al. (2010) and Chester et al. (2010). Embodied energy for surface lots was calculated as for roadways, using GIS land-use data and City of Austin design parking space design standards. In some cases, GIS data excluded some private parking spaces, mostly for apartment and townhome buildings. These additional spaces were estimated using City parking requirements (one parking space required for single-bedroom units, and 0.5 spaces required for each additional bedroom per unit).

The final components considered for embodied infrastructure impacts are water and wastewater pipes. Their locations, materials, and diameters are available through the City of Austin[5], and were tabulated for each neighborhood. Pipe material lifespan are

[5] The City of Austin provides a large amount of GIS data at ftp://ftp.ci.austin.tx.us/GIS-Data/Regional/coa_gis.html. Water and wastewater data was made available upon email request.

based on estimates by Seiders et al. (2007) and embodied energy estimates from Hammond and Jones (2010).

2.4.2 Residential and Commercial Buildings Embodied Energy

Life-cycle analyses include a great deal of uncertainty, even when analyzing just one material or structure. Since this paper's LCA approach evaluates multiple materials and building types, each with unique construction techniques and input sources, it becomes very difficult to ensure accuracy and precision (Lloyd and Ries 2008). However, general estimates of average energy consumption still provide a useful metric when held constant across several different neighborhood types. Rather than perform a detailed LCA, by either estimating all building materials for countless buildings, or attempting to perform an economic input-output LCA (Hendrickson et al. 1998, Finnveden et al. 2009), this analysis assumes an average rate of embodied energy per square foot, by building type.

Building type and base footprint were collected for each of the four neighborhoods using Google Earth data, and total built area (per building) came from visual inspection of the number of stories per building, using Google's StreetView imagery. Embodied energy was assumed to be 0.5 GJ/ft^2 for single-family homes, 0.6 GJ/ft^2 for multi-family homes, and 0.65 GJ/ft^2 based on an analysis by Hammond and Jones (2010).

2.5 Energy Elasticities

Accounting for energy consumption sources across neighborhoods offers insight into the relative impacts of different sectors across land-use styles, but does not necessarily identify how specific land-use and behavioral changes can impact total energy use.

Computing elasticity values allows one to anticipate impacts from changes in model parameters. In this case, elasticities were computed to estimate how energy consumption (in operational and embodied stages, and in total) responds to specific changes in the BE or user behavior. Elasticity estimates have been very informative for identifying impacts of BE changes on travel demand, but such analyses rarely extend to include holistic energy impacts. For instance, Ewing and Cervero (2010) reviewed nearly 200 studies to compute weighted-average elasticities for vehicle miles traveled (VMT), non-motorized travel (NMT), and transit responses to changes in BE variables, but it is often unclear exactly how these impacts affect total energy. Especially important here is the phase under which impacts might occur (operational or embodied). For instance, increasing density may reduce VMT and therefore reduce operational demands, but will also decrease per-capita embodied energy demands. Understanding the individual sources and aggregate impacts of life-cycle energy savings becomes an informative extension of elasticity analysis.

Wherever possible, new "energy elasticities" were computed here, by changing BE variables used directly by the LCA model, such as population and jobs density, SFH shares, residential unit size, building age, gasoline price, and bus occupancy. Effects of some other important BE metrics (not directly computed for each neighborhood), such as land-use mix and regional accessibility, were also considered here, by simply pivoting off VMT percentage changes (using Ewing and Cervero estimates [2010]), after assuming a base/reference (accessibility or mix) value for each neighborhood.

Overall, separate elasticities ($\eta_{i,j}$) were computed for each energy "phase" i (operational, embodied, or total life-cycle energy), for several BE variables (x), via the following equation:

$$\eta_{i,x} = \left|\frac{\Delta E_i}{\Delta x} \times \frac{x}{E_i}\right|$$

where E_i is the energy use for phase *i.* The resulting energy elasticities provide context for how much transportation, land use, and home efficiency policies and programs fare, across neighborhoods. They allow one to extend earlier, context-specific evaluations (e.g., of BE attributes on VMT) to larger-scale energy analyses.

CHAPTER 3 : NEIGHBORHOOD ENERGY USE PATTERNS

Transportation and household energy use calculations below illustrate how BE characteristics significantly influence (expected) vehicle purchases, driving choices, transit use, and heating and cooling demands. Since all neighborhoods assume a demographically uniform population, variations of per-capita impacts across neighborhoods can be attributed to population and jobs densities, housing style, and urban location (i.e., distance to Austin's CBD) and residential unit size. In reality, demographic variations may produce even greater variations across these four settings, since income, household size, number of workers, and other variables significantly impact behaviors, as indicated by model parameters.

3.1 RESIDENTIAL NEIGHBORHOOD LIFE-CYCLE ENERGY USE ESTIMATES

The five case neighborhoods clearly vary in their required infrastructure and (expected) travel behaviors (assuming the same set of households residing in each). Table 3.1 presents their overall residential energy consumption estimates, for operation versus embodied energy, and uses relating to transport, buildings, and infrastructure.

Table 3.1: Operational Energy (GJ/ capita/year)

		1R-WL	2R-AM	3R -HP	4R –RS	5R-DT
Transport Sources	LDV Fuel Use	48.25	45.43	36.58	25.18	6.89
	Transit Fuel Use	0.57	0.41	0.23	0.29	0.07
	Parking Garages	--	--	--	--	--
	Surface Parking	--	--	--	--	--
	Sidewalks	--	--	--	--	--
	Streets & Roads	--	--	--	--	--
Building Sources	Res. – SFH	51.24	47.79	39.73	34.89	39.23
	Res. – Duplex					
	Res. – Apt.					
Infrastructure Sources	Freshwater	0.39	0.39	0.39	0.39	0.39
	Wastewater	0.15	0.15	0.15	0.15	0.15
	Lighting	0.40	0.29	0.10	0.07	1.12
Transport	Sub-Total	48.82	45.84	36.81	25.47	13.78
Buildings	Sub-Total	51.24	47.79	39.73	34.89	39.23
Infra.	Sub-Total	0.94	0.83	0.64	0.61	1.66
Grand Total		101.0	94.46	77.18	60.97	40.89

Table 3.2 Embodied Energy Estimates (GJ/capita/year)

		Embodied Energy				
		1R – WL	2R – AM	3R – HP	4R – RS	5R – DT
Transport Sources	LDV Fuel Use	--	--	--	--	--
	Transit Fuel Use	--	--	--	--	--
	Parking Garages	0.00	0.00	0.06	0.00	0.01
	Surface Parking	0.00	0.00	0.35	1.00	0.01
	Sidewalks	0.05	0.31	0.09	0.04	0.07
	Streets & Roads	8.66	10.82	6.01	2.28	2.49
Building Sources	Resid. – SFH	13.97	9.63	3.86	0.23	0.06
	Resid. – Duplex	0.04	0.00	0.20	0.03	0.00
	Resid. – Apt.	0.79	1.01	1.08	3.57	0.86
Infrastructure Sources	Freshwater	0.34	0.25	0.20	0.23	0.12
	Wastewater	0.14	0.12	0.14	0.03	0.16
	Lighting	--	--	--	--	--
Transport	Sub-Total	8.71	11.13	6.51	3.32	2.58
Buildings	Sub-Total	14.8	10.64	5.14	3.83	0.92
Infra.	Sub-Total	0.48	0.37	0.34	0.26	0.28
Grand Total		23.99	22.14	11.99	7.41	3.78

Average households from the two suburban neighborhoods (R1-WL and R2-AM) are expected to drive more miles, own more vehicles, and purchase more SUVs or CUVs, trucks, and vans, than passenger cars. Average fuel economy is relatively constant across neighborhoods due to a lack of BE-sensitive variables in the fuel economy OLS model.[6] The households' LDV energy use levels come directly from a fuel-use model (total gallons, based on household VMT and fuel economy in the NHTS data set), which, as expected, predicts the largest per-household gasoline consumption for R1-WL, followed closely by R2-AM. Essentially, fewer miles driven, fewer vehicles owned in general, and a lower concentration of lower-fuel-economy vehicles (vans, SUVs, and trucks) are associated with the higher density neighborhoods (R5-DT and R4-RS) and the neighborhood with mixed SFH/MFH units (R3-HP).

Comparing the final rows of Tables 3.1 and 3.2 show how the majority (83 to 92%) of annual residential energy requirements can be attributed to a setting's operational demands, such as driving and home energy use. Tables 3.1 and 3.2's columns also show how the suburban neighborhoods (1R-WL and 2R-AM) require the most energy per capita, in terms of individual operational and embodied demands, and overall life-cycle uses.

Predictions of person-miles traveled on transit modes are also interesting, though the findings may not be practically significant for these chosen neighborhoods. In general, transit miles used per household were quite low in all four neighborhoods, which is consistent with Austinites' existing travel patterns. The behaviorally-based regression models for transit use suggest that the suburban neighborhoods of R1-WL and R2-AM

[6] BE variables from NHTS data (e.g., population, housing, and employment density, urban setting, rented vs. owned home shares) were found to be insignificant well beyond p-values of 0.1.

will generate nearly the same number of transit-trip-miles as R4-RS – and more than those in R3-HP. Due to the greater distances, suburban travelers with fewer stop options per square mile, end up experiencing longer transit trips (according to the NHTS data sets, ceteris paribus), when they do take transit. Thus, despite a lower *number* of transit trips per household or per capita in these suburban areas (neighborhoods R1 and R2), their longer trip lengths largely equalize the total number of passenger miles traveled (PMT) by transit. In reality, Austin' Capital Metro transit coverage does not actually include the Anderson Mill (R2-AM) neighborhood (so transit miles there are zero) and is very sparse in the Westlake (R1-WL) area, and actual ridership will be even lower for residents of those two neighborhoods.

Separating total impacts by source illuminates the relative magnitude of transportation sources, versus buildings and other infrastructure (namely water, wastewater and municipal lighting). Figure 3.1 shows how annual fuel use for personal transport, along with embodied energy required to build and maintain streets, sidewalks, driveways, surface parking, and parking structures, can comprise from 40 to 46% of total life-cycle energy across these neighborhoods. Building energy use, for heating, cooling, appliances, electronics, and other uses, along with embodied energy for building materials and construction and maintenance, comprise nearly all the remaining portion of life-cycle energy use by these settings' residents: roughly 53 to 55% of the totals computed here, across all four neighborhood cases. The remaining uses (water usage, water and wastewater pipes, and lighting) may represent a significant municipal cost, but appear insignificant in these residential contexts.

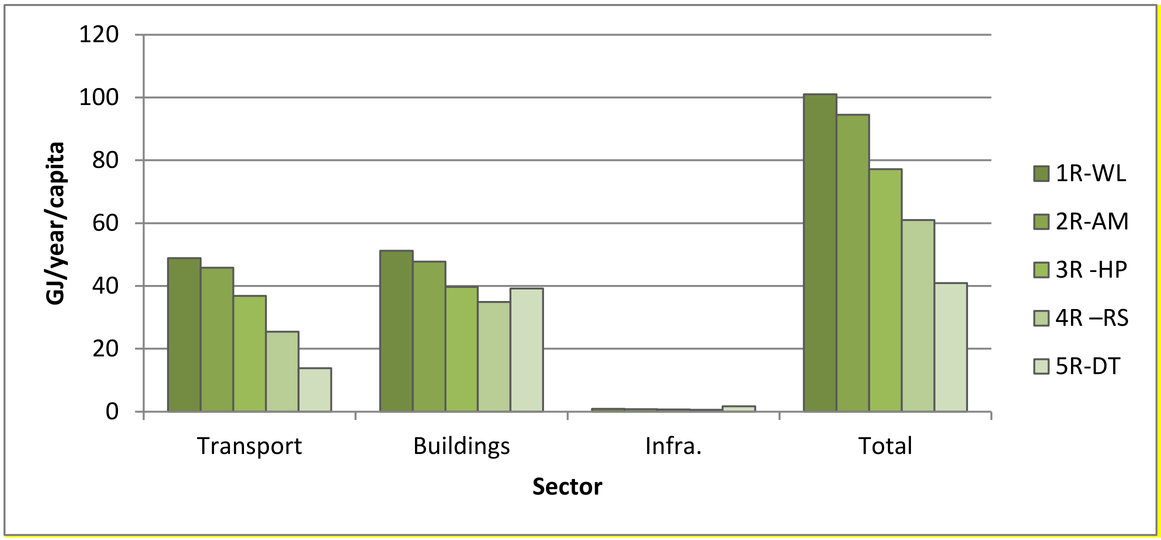

Figure 3.1: Neighborhood Life-Cycle Energy Demands by Sector

Figure 3.2 demonstrates energy use by phase, suggesting that the majority of life-cycle use can be attributed to the operations phase. Results suggest that embodied energy ranges from 8 to 19% in these neighborhoods, with shares generally falling with density and proximity to downtown.

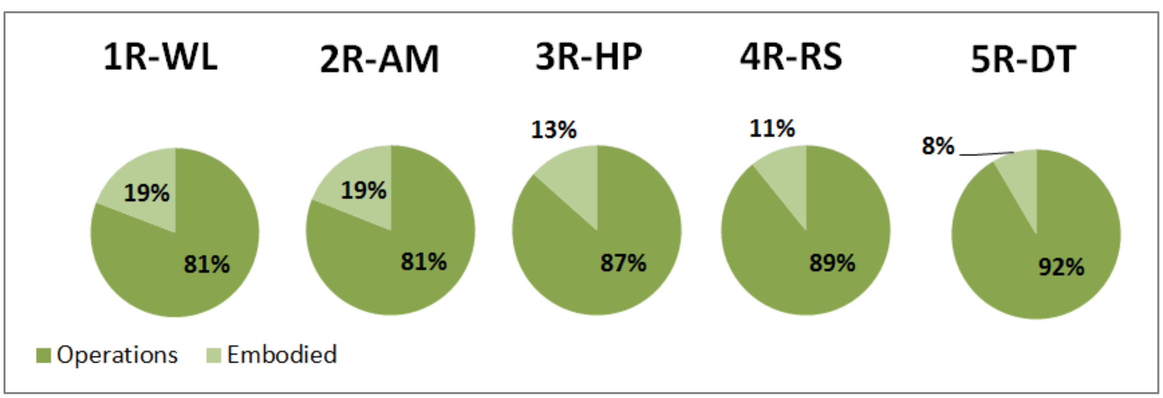

Figure 3.2: Neighborhood Life-Cycle Energy Demands by Phase

Of course, this analysis ignores these households' energy demands while at work, school, the gym, and other settings; while traveling by air or boat; and when consuming clothing, food, and other goods, for example. But such energy demands may be expected to be rather comparable across this same set of households, regardless of their home location choice. The share of these buildings types varies across neighborhoods surveyed here, so they were excluded to maintain consistency. However, jobs-housing mix does impact travel behavior (Cervero 1989, Kockelman 1997) and therefore transportation energy, so some of these BE effects are not captured.

Additionally, this analysis does exclude other energy use from industrial demands, along with commercial travel, shipping and other energy demands. Industry alone consumes over 30% of the nation's energy, and freight may consume about 10% of total energy, leaving 40% of total energy uses unaccounted for in this analysis. However, as previously mentioned, these energy users are generally outside the scope of urban design and policy evaluations, so residential and commercial sources are emphasized here.

3.2.1 Influence of Residential Neighborhood Demographics

Since this study identifies neighborhood energy-use differences based on design characteristics, uniform populations have been assumed to isolate physical differences from demographics. For instance, most models and energy equations previously estimated do depend on household features such as income, size, and number of adults, indicating that energy use changes with both the built environment alone (as seen in above results) and household demographics. In order to understand which factors influence energy use most (either demographics or urban design), the above results are compared to model results with actual demographics for the five model neighborhoods. This is performed simply be re-estimating models for the largest energy-consuming sources seen above – LDV fuel use and home energy use (from electricity and natural gas combined). Whereas a panel of different household types was used before, only the average neighborhood characteristics are considered here, as shown in Table 3.3.

Table 3.3: Actual Neighborhood Demographics and Model Estimates

	1 – WL	2 - AM	3 - HP	4 - RS	5 - DT
Measured Values					
Population Density (per mi^2)	961	6,148	5,713	17,249	4,858
Median Household Income	$168,625	$76,616	$34,743	$25,446	$52,602
Adults per Household	2.79	2.86	1.75	2.15	1.85
Urban Area Indicator	0	0	1	1	1
Model Estimates (Using Above Values)					
Fuel Use per Vehicle (gallons/year)	451.43	428.42	452.31	423.36	243.87
Avg. LDV Fuel Economy (mpg)	23.15	23.23	23.87	24.29	23.88
Household Vehicle Count	2.89	2.77	1.31	1.05	0.54
LDV Energy Use (GJ/year/capita)	**71.2**	**62.6**	**32.0**	**24.0**	**6.8**
Electric + Natural Gas Energy Use (GJ/year/capita)	**64.1**	**57.6**	**55.7**	**44.3**	**41.4**

These values indicate a significant difference in household income and household size across these neighborhoods, though constant (region-wide) averages were used in some places where data was unavailable. The primary difference in this approach is the average household income difference across neighborhoods. Model estimates from Table 3.3 indicate that incorporating these few variables produces results significantly unique from constant neighborhood demographics. These results are compared against uniform-population neighborhoods, for LDV and electricity and natural gas usage in Figures 3.3 and 3.4, respectively

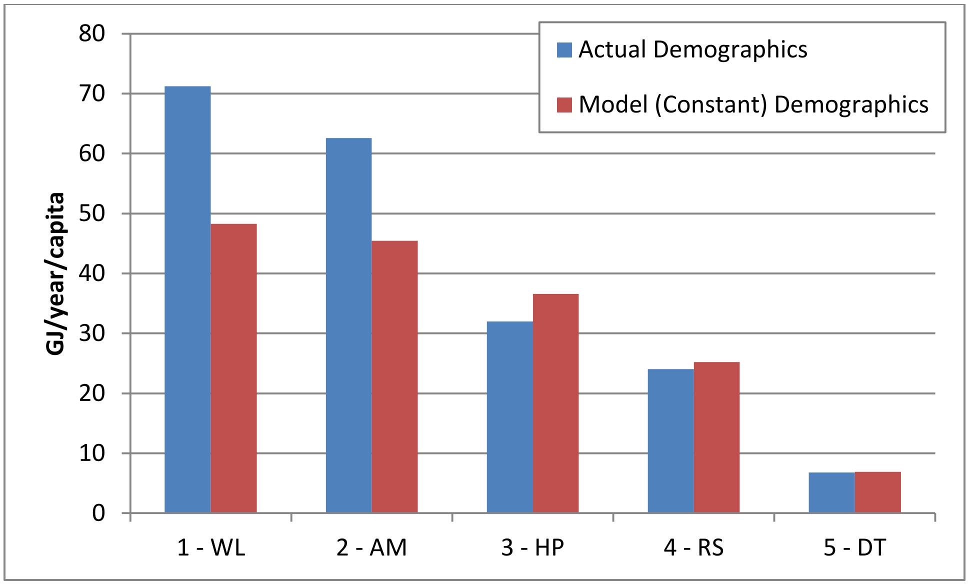

Figure 3.3: LDV Energy Use with Constant and Varying Neighborhood Demographics

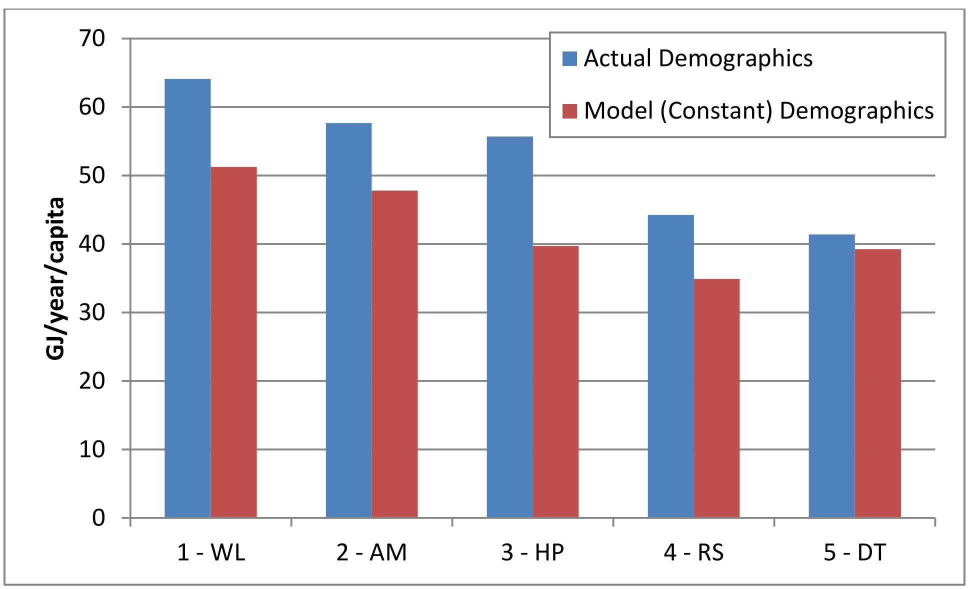

Figure 3.4: Electricity & Natural Gas Energy Use of Constant and Varying Neighborhood Demographics

These results indicate the relative impact of demographics (specifically income and number of adults) on energy use, across the neighborhoods and provide a sense of how much energy demands are being excluded by considering constant neighborhood demographics. Variations between actual and constant demographics demands are most pronounced in the two most suburban neighborhoods (R1-WL and R2-RS), for both LDV and electricity and natural gas energy use. This result suggests that while the BE influences energy use, as seen in previous results, a sizeable portion of total household energy use does depend on specific household demographics. Therefore, shifting larger, wealthier households into smaller homes in denser neighborhoods may reduce energy less than anticipated from the "constant demographics" neighborhood estimates. Alternatively, the models also suggest that relocating less wealthy families into larger homes may not necessarily result in energy usage equivalent to wealthier families in the same home typ.e Altogether, this analysis suggests that the BE influences only a portion of household energy use, and that a significant portion of energy use, based on household demographics, may not be controllable by the residential environment.

3.2 Commercial Neighborhood Life-Cycle Energy Use Estimates

Table 3.3 presents results for commercial neighborhoods in a similar fashion to those for residential neighborhoods, combined into a single table. For commercial neighborhoods, estimates are presented on a "per-job" basis, to maintain consistency across different commercial neighborhood styles.

Table 3.4: Commercial Neighborhood Life-Cycle Energy Estimates (GJ/job/year)

		Operation			Embodied		
		1C-RS	2C-HP	3C –DT	1C-RS	2C-HP	3C –DT
Transport Sources	Parking Garages	--	--	--	0.00	0.03	0.00
	Surface Parking	--	--	--	1.44	0.20	0.00
	Sidewalks	--	--	--	0.05	0.05	0.02
	Streets & Roads	--	--	--	3.28	3.39	0.65
Building Sources	Commercial	31.70	28.42	26.02	1.19	0.61	0.22
	Office				0.00	0.16	1.23
Infrastructure Sources	Freshwater	0.48	0.18	0.02	0.32	0.11	0.03
	Wastewater	0.18	0.07	0.01	0.04	0.08	0.04
	Lighting	0.09	0.04	0.06	--	--	--
Transport	Sub-Total	0.00	0.00	0.00	4.77	3.67	0.67
Buildings	Sub-Total	31.70	28.42	26.02	1.19	0.77	0.45
Infrastructure	Sub-Total	0.75	0.29	0.09	0.36	0.19	0.07
Grand Total		**32.45**	**28.71**	**26.11**	**6.32**	**4.63**	**1.19**

These results suggest that the majority of life-cycle energy used in these commercial neighborhoods is attributable to operational uses, rather than embodied energy, as shown in Figure 3.3.

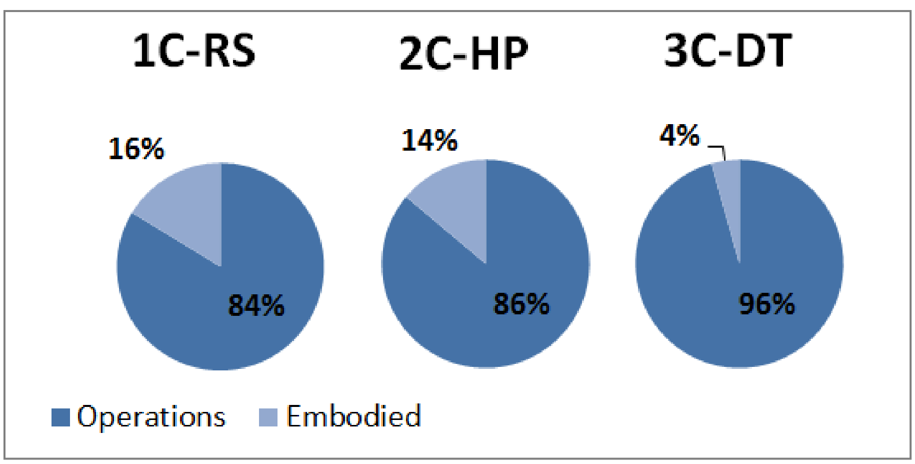

Figure 3.5: Life-Cycle Commercial Neighborhood Demands by Phase

Figure 3.4 compares results from Table 3.3 visually, indicating the slight per-worker decreases in energy consumption across the three commercial neighborhood types. The results suggest that the nearly all commercial energy use is operational in nature, and that the associated infrastructure contributes a relatively small portion of commercial energy demands. However, it should be noted that this framework assigns all transportation energy to the residential sector, such that households produce all trips, even though a large share of those are commute trips. Trips for work and shopping could just as easily be assigned as part of the commercial sector's operational energy demands, given a share of trips (and commute distance distributions). Therefore, comparing commercial and residential sectors in the current framework is not fair, and should rather be used to compare different commercial neighborhood styles and energy use phases alone. Future research should consider trip purposes more carefully, as well as estimate freight and commercial trips generation, for a more equitable and holistic comparison.

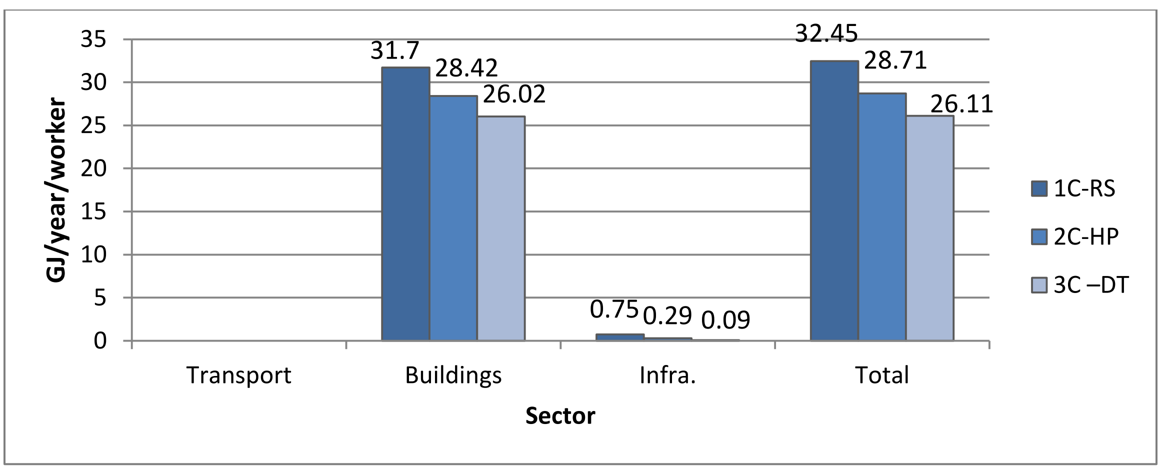

Figure 3.6: Operational Energy Demand Estimates for Commercial Neighborhoods (per job)

3.3 Energy-Savings Policy Focus: Energy Elasticity Estimates

While it is informative to quantify and compare the sources of life-cycle energy use across existing neighborhoods, it is even more important to consider which energy-saving strategies could best be implemented. For instance, reducing LDV fuel use and home energy consumption may be logical targets, but it is often unclear which strategies are most cost-effective. Elasticity estimates help guide such analyses, by exploring (model-predicted) energy use changes, following changes in various BE characteristics (via the energy elasticities described earlier). Table 3.4 reports the resulting elasticities for variables considered directly in the behavioral sub-models, along with some other important BE metrics (like regional accessibility and land use mix). The first set of elasticity values corresponds to model-integrated variables that can impact vehicle ownership, VMT, home energy use, and/or the amount of residential structures and infrastructure (for embodied energy calculations). The latter set relies on VMT- specific elasticities from Ewing and Cervero (2010).

Table 3.5: Energy Elasticity Estimates

	Operational Energy				Embodied Energy			
	1-WL	2-AM	3-HP	4-RS	1-WL	2-AM	3-HP	4-RS
Directly Modeled Variables								
Population Dens.	-0.01	-0.03	**-0.19**	**-0.09**	**-0.91**	**-0.77**	**-0.58**	**-0.60**
Housing Unit Dens.	-0.00	-0.03	**-0.06**	**-0.14**	+0.01	+0.03	+0.03	**+0.09**
Employment Dens.	-0.02	-0.01	-0.03	-0.02	0.00	0.00	0.00	0.00
% Residential SFH	-0.01	-0.01	-0.02	0.00	**+0.62**	**+0.49**	**+0.29**	+0.03
Resid. Building Age	**+0.05**	**+0.05**	**+0.05**	+0.04	0.00	0.00	0.00	0.00
Resid. Unit Size	**+0.12**	**+0.08**	**+0.05**	**+0.06**	**+0.56**	**+0.53**	**+0.40**	**+0.47**
Gasoline Price	-0.04	-0.04	-0.04	**-0.06**	0.00	0.00	0.00	0.00
Avg. Bus Occ.	0.00	-0.01	-0.01	-0.01	0.00	0.00	0.00	0.00
Other BE Variables								
Land Use Mix	-0.02	-0.02	-0.02	-0.02	0.00	0.00	0.00	0.00
% 4-way Intersections	-0.03	-0.03	-0.02	-0.03	0.00	0.00	0.00	0.00
Job Accessibility (via automobile)	-0.05	-0.05	-0.04	-0.05	0.00	0.00	0.00	0.00
Job Accessibility (transit)	-0.01	-0.01	-0.01	-0.01	0.00	0.00	0.00	0.00
Distance to CBD	-0.05	-0.06	-0.04	-0.06	0.00	0.00	0.00	0.00
Transit Stop Accessibility	-0.01	-0.01	-0.01	-0.01	0.00	0.00	0.00	0.00

Table 3.4’s values are useful for identifying which design and policy parameters have greatest influence over energy use, by neighborhood type, and across operational or embodied sources. It seems that embodied energy is greatly affected by population density, resulting in very sizable overall life-cycle energy impacts. Similarly, average living space increases day-to-day energy consumption, but it is this variable’s embodied energy impacts (associated with more building materials) that have the greatest impact on total energy expenditures. Together, these two variables, Population Density and

Residential Unit Size, are estimated to have the greatest practical impacts on energy use, in terms of average elasticities, across a wide variety of residential settings.

In some others cases, embodied energy impacts are negligible. For instance, higher gasoline prices and bus occupancy levels offer slight savings in operating-energy use, but have lower elasticities for overall energy use after incorporating their assumed non-existent embodied-energy impacts. Such moderate impacts also emerge for the indirectly estimated, VMT-based changes. Elasticity estimates for this latter set of neighborhood attributes presumes that their changing does not impact infrastructure design and embodied energy levels; in reality, however, increased job accessibility and rising land use mix are likely to come with increases in density and smaller residential units (and less commercial space per worker, for example). The elasticities computed here suggest that by doubling, for instance, job accessibility by automobile, the resulting (estimated) 20% decrease in VMT may provide a 4% (operational) energy use savings and total (life-cycle) savings of roughly 2%, for a specific neighborhood. To better reflect the marginal impacts of these VMT-focused BE variables, a study that quantifies each neighborhood's accessibility, mix, and other attributes, and then controls for these in one or more of the LCA sub-models is needed. Such studies may find greater (marginal) impacts (holding all other variables constant). It also is likely that the variables of population (and jobs) density, %Residential SFH, and Residential Unit Size are partly proxying for facets of these other BE variables, so these important model inputs' impacts (and elasticities) will probably diminish once more BE attributes are controlled for, in the behavioral sub-models.

3.4 Sensitivity Analysis

Though elasticities provide relative sensitivity of specific variables, this can be measured more directly with a sensitivity analysis for specific parameters. Results above indicated that driving and household energy use from electricity and natural gas were primary energy-consuming sources, yet these can be highly variable across households within each neighborhood, as some families may own a very-fuel efficient hybrid (or even a plug-in electric vehicle) while others may own larger SUVs. Among these households, some vehicle owners may seldom drive or drive excessive amounts, based on unobserved factors. The variation is important to consider in order to more comprehensively compare neighborhoods.[7] Figure 3.7 considers LDV energy use with ranges in VMT increase or decrease, ranging from 75% less than modeled average to 75% more.

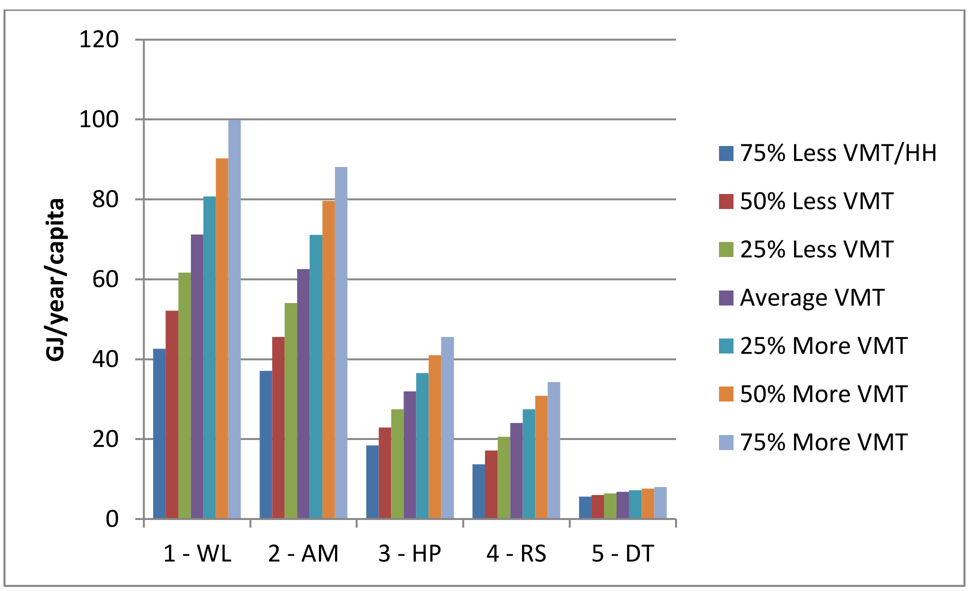

Figure 3.7: Annual LDV Per-Capita Energy Use with VMT Ranges

[7] These sensitivity analyses are based on actual neighborhood demographics results (see Section 3.2.1) to capture more realistic behavioral variations.

This result suggests that the more suburban neighborhoods are subject to more extreme variations in per-capita energy consumption, and that even with significant VMT reductions (50 to 75%), these neighborhoods still consume more LDV energy per capita than the other neighborhoods. Even with an excessive driving increase, the other neighborhoods would not reach averages for the two suburban neighborhoods.

A similar result is observed by adjusting average household fuel economy (while holding all other variables constant), as shown in Figure 3.8.

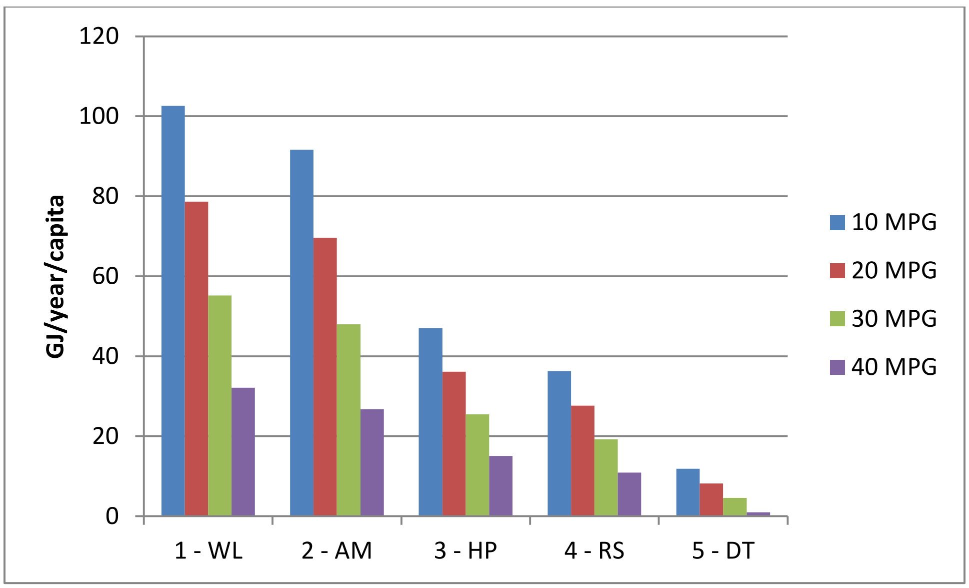

Figure 3.8: Annual LDV Per-Capita Energy Use with Fuel Economy Ranges

This result closely resembles that of Figure 3.7, but does suggest that larger, more suburban neighborhoods (R1-WL, R2-AM) might reduce their overall demands to those of neighborhoods R3-HP and R4-RS, with highly fuel-efficient vehicles, averaging 30 to 40 miles per gallon. This result is rather encouraging news, considering future CAFÉ standard guidelines are poised to raise U.S. fuel economy substantially (54.5 mpg by 2025). However, this shift will likely impact all neighborhood households over time, maintaining the imbalance across neighborhoods, unless VMT changes significantly. Even with aggregate increases in fuel economy, possible rebound effects of increased driving with improved efficiency (or lower fuel prices) may maintain this difference across neighborhoods.

In addition to LDV use, another variable component is electricity and natural gas usage. Figure 3.9 shows how this energy-use sector depends on average household size, within each neighborhood, to capture building structure diversity.

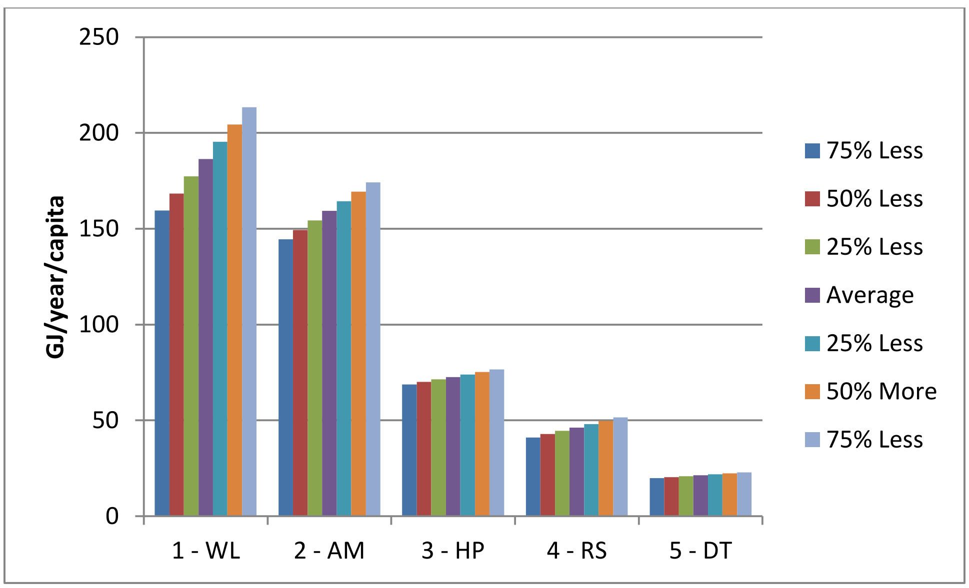

Figure 3.9: Annual Electricity & Natural Gas Per-Capita Energy Use with Residential Unit Size Ranges

This result suggests that average home sizes are quite different across neighborhoods, and that even with rather sizeable changes in living space, households (electricity and natural gas) energy usage is not comparable across different neighborhoods, and is rather more a function of demographics. Though some neighborhoods have the opportunity to reduce their LDV energy demands (via increased fuel economy) to compete with other more dense neighborhoods, energy use from suburban households will usually be more intense than those of more urban neighborhoods. However, this sensitivity analysis is rather limited in the variables it considers, especially for electricity use. A more detailed electricity use model might capture efficiency benefits of highly-efficient home appliances or building designs that do allow these neighborhood settings to compete with denser locations with more multi-family housing units.

3.5 Conclusions on Neighborhood Energy Estimates

This analysis provides a holistic approach for evaluating the long-term energy impacts of different neighborhood types, and creates some metrics that help evaluate how land-use and transportation designs and policies may impact energy use at the neighborhood level, and even higher (larger) spatial scales. By evaluating a diverse set of real-world neighborhoods, this work quantifies energy savings from different land-use patterns. While some of the results developed here may best apply to only the four Austin neighborhoods evaluated, it is likely that most (if not all) of the general trends uncovered here can be extrapolated to other cities and settings. Certainly, the methods, model framework, and metrics used here can be employed elsewhere. This work's major achievement lies in disentangling a complex set of urban subsystems and compiling energy estimates via interconnected models and careful visual and GIS analysis. This work provides a framework for evaluating new and existing neighborhoods – of any kind, making extensions a natural possibility.

Most energy-reduction policies focus on reducing VMT or improving building efficiencies, but this analysis shows that between 8 and 17% of life-cycle energy can be attributed to the BE's embodied energy impacts in the four residential neighborhoods examined here. These more compact, higher-density developments provide opportunities to reduce both VMT (and thus transportation's energy demands) and embodied energy. In the most extreme case, the traditional suburban neighborhood examined here (R2-AM) required up to 3.2 times the embodied energy (per capita) of the densest neighborhood (R4-RS) and 1.6 times its total (life-cycle) energy. Even if Neighborhood 2's operational energy demands were to remain constant, changing its BE attributes to match those of Neighborhood 4 (Riverside), could reduce annual total energy use by nearly 5%, simply by reducing embodied energy demands. Such energy savings are not easy to estimate, and this analysis offers a more holistic view of how neighborhood design can impact energy consumption.

Energy elasticity calculations suggest that changes in two important BE variables, population density and residential unit size, can trigger the greatest per capita energy savings. These are critical policy variables that can be used to drive energy efficiency in future developments by way of astute planning and zoning policy, and municipal infrastructure investments that align with density and sizing goals. Density and unit sizing are the most energy-responsive BE variables in this analysis, and should be regarded as one of the most efficient approaches in reducing life-cycle urban energy use. This evaluation also illuminates how most improvements in energy efficiency must come through reduced fuel consumption and less energy-intensive transportation infrastructure, including parking facilities and roadways. Altogether, fuel use and transportation infrastructure comprised around 45% of life-cycle energy demands across the distinctive residential neighborhoods examined here (both real and simulated/extrapolated [for elasticity computations]). Since per-capita VMT in the U.S. has been falling recently and vehicle fuel economies are improving (thanks to rising Corporate Average Fuel Economy standards), such a statistic is rather encouraging, since it indicates reachable goals of energy reductions in the near future.

In summary, there are many opportunities to improve urban energy efficiency, and thoughtful BE planning and transport policy can improve aggregate energy efficiency and reduce associated environmental, societal, and economic impacts. Taking a life-cycle perspective on energy analysis provides more context on how density and residential building styles impact total energy use. While operational energy from driving and electricity and natural gas use are the major consumption sources in neighborhoods, their estimated rates varied significantly across neighborhood types in Austin, with the least efficient neighborhood consuming nearly twice the total energy per-capita as its most efficient counterpart. Combined with the fact that embodied energy estimates comprise between 8 and 17% of total life cycle energy, this study suggests that development patterns can have a significant impact on energy consumption rates.

3.6 Future Work and Caveats

Though this work contributes rather comprehensive neighborhood energy use estimates, future work should incorporate more modeling variability to better capture the uncertainty associated with both embodied and operational energy calculations, and many other assumptions such as material and building lifetimes. In reality, all calculations here are subject to potentially large variability that could alter some of the conclusions reached here. For instance, perhaps some denser neighborhoods contain families that drive much more or use much more energy-intense materials, making them more energy-intensive than a suburban neighborhood with very high concentrations of fuel-efficient vehicles and/or exceptionally energy efficient homes. Such cases should truly be considered before broad conclusions can be drawn from the energy-use implications of different neighborhood styles.

Another important extension of this study would be to translate energy use into greenhouse gas emissions. Greenhouse gas (GHG) emissions cannot be extracted directly from energy consumption, without knowing power grid fuel sources (though conventional, gasoline-powered vehicles' GHG impacts can be estimated directly from fuel use and fuel economy models developed here). Additionally, embodied GHG emissions estimates would also be required, since electricity is required for many manufacturing, production, and construction processes. Therefore, future studies could extend this work to include GHG impacts, by evaluating GHG impacts of various power grid mixes.

Finally, future work could also incorporate more emphasis on cost comparisons between different neighborhood forms, by estimating different material costs for the embodied phases, maintenance costs over the life of the building or material, and daily operation costs. These estimates are critical to implementing policy and effecting desired consumer behavior (such as purchasing more energy-efficient appliances or investing in upgrades to more efficient heating and cooling systems) and are thus the next logical step in a comprehensive policy analysis of different built environments. Though some general work considers costs of different built environments (Burchell et al. 2002) and cost-savings of different GHG emissions control strategies (Kockelman et al. 2008), extending this analysis to consider cost differences would be a natural (and critical) extension.

CHAPTER 4 : CITY-SCALE ENERGY USE PATTERNS

4.1 City Life-Cycle Energy Model Development

The set of five residential and three commercial settings, can be combined in various ways to produce a life-cycle energy analysis at a larger, city-scale scope. Though much more variation occurs in reality, these 8 neighborhood types represent a range of built environment types in a typical city – from sparse single-family home developments to more dense downtown environments and mixed styles in between. In the model, commercial and residential cells are independent, so a cell may have high density housing with a lower density commercial cell, or no employment or residential centers at all. (In the synthetic cities, however, worker-resident ratios and are held constant, and actual population and employment values matched as possible to maintain consistency.)

This chapter focuses on holistic energy demands for residents and workers in different urban settings, and identifying how density patterns influence aggregate emissions rates. The analysis incorporates several "building blocks" from different disciplines (travel demand, buildings energy, infrastructure, LCA) to construct larger neighborhoods, and finally city patterns. A set of sub-models works together to create a group of neighborhoods in different urban form, to reflect the form of actual U.S. cities. Modeled energy use, by source and phase are evaluated and compared to infer the impact of the built environment on large-scale energy demand.

4.1.1 City Model Structure

This city model considers a monocentric gridded cell city model, with square cell areas of 1 mi^2. The model area contains a 10-mile radius from the city center, and a circular area described by the midpoint circle algorithm, for a total grid area of 308 mi^2. The midpoint circle algorithm determines which cell centroids are within given a given radius, so one-mile distance bands can be created around the city center, as shown in Figure 4.1, with cell numbers indicating miles from city center.

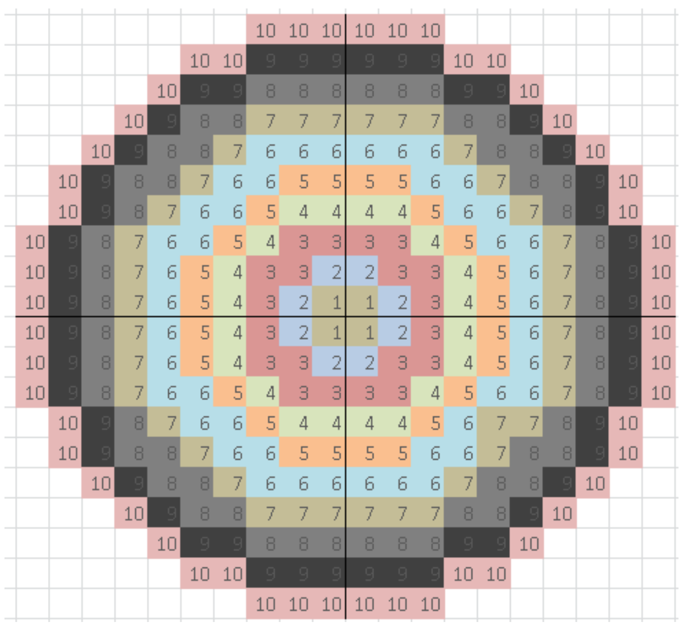

Figure 4.1: Model City Form with Distances from City Center Marked for each Cell.

Using this construct, two city forms are considered – one for residential neighborhood type distribution, the other for commercial neighborhoods. Energy (for operations vs. embodied, residential vs. commercial, transportation vs. infrastructure vs. buildings) is then tabulated for the city area, based on residential and commercial neighborhood attributes. Total population ($p_{i,j}$) and number of workers or employees ($e_{i,j}$) per cell *ij* is calculated as a function of underlying neighborhood population and employment densities (ρ_r and ρ, respectively) and cell area ($A_{i,j,}$) as follows:

$$p_{i,j} = \rho_r A_{i,j}$$

$$e_{i,j} = \rho_c A_{i,j}$$

Of course, cell area is kept constant at 1 mi^2, so the total number of residents and employees is therefore equal to population and employment density (on a per-square mile basis). In addition to population and employment density distributions over space, job accessibility ($AI_{i,j}$) is also computed using a gravity-based index as follows:

$$AI_{i,j} = \sum_{m,n} (e_{m,n} \times c_{m,n}{}^{\upsilon})$$

Index *m,n* is used to differentiate cell locations for the summation across the grid for each accessibility calculation for each cell of focus (home or job zone cell *ij*). Average travel costs between zone *ij* and any other zone *mn* is represented by $c_{m,n}$, in terms of Euclidean distance in miles. The υ term is a gravity parameter or friction factor to reflect falling accessibility as a function of travel cost. In this model, a friction factor of -0.35 is used based on calibration to San Francisco data (Cervero et al. 1999). The accessibility model used here considers a very simple and linear travel cost function based on cell centroid distances, as follows:

$$c_{m,n} = \sqrt{(x_i - x_{m)}{}^2 + (x_j - x_n)^2} + r$$

where *r* is half the cell width (or the radius of an inscribed circle within each 1-mile cell and added to ensure the $c_{m,n}$ always exceeds zero and returns a valid accessibility value (since zero cannot be raised by a negative exponential υ). This value also represents the average distance traveled within a cell to reach a local destination within the same cell (i.e., accessibility within a cell is generally not free of travel cost, and intra-cellular travel is assumed to be a function of the average distance of that cell). Since cell sizes are 1 mi^2 here, $r = 0.5$.

4.2 Modeling Case Study Cities

The base city model considered here is Austin, the city from which the neighborhood cells were originally created. Four other cities are then also considered, including the lower-density regions of Orlando, Florida and Phoenix, Arizona, and higher-density settings of Seattle, Washington and New York, New York. It should first be noted that these models are not intended to represent actual energy demands of Seattle or Orlando, but rather explore the results of distributing these Austin-style neighborhoods in different ways. In other words, by arranging the eight different Austin neighborhoods in ways to resemble other cities, how might the resulting energy demands compare? For instance, to approach a New-York-style environment with only the current neighborhood “tiles”, Austin would consist of only the densest residential and commercial neighborhoods. This would certainly not reflect an actual model of New York (since even the most dense Austin neighborhood is much less dense than the average of New York), but the exercise explores rather extreme approaches of built environment styles.[8]

Model creation is initially performed manually and rather intuitively, to best match existing neighborhood styles viewed from satellite imagery with the bank of eight cells

[8] In most cases, the Austin neighborhood cells are able to very closely mimic other regions’ average resident and employment density profiles, with the exception of New York City. Only in this extreme example are actual density profiles never achieved, so a maximum-density case was constructed instead, based on the maximum densities the Austin neighborhoods could provide.

types. Population and employment density, and accessibility trends are a function of distance from city center and matched with the model city as closely as possible, by changing neighborhood types along each distance band. For instance, if Austin's population density within the first mile radius of the city center is 20 residents per acre, a set of neighborhoods is filled in the model cells to best reflect that density. The approach is otherwise rather subjective on which exact cells to fill with neighborhood cell types (and bounded only by rational replication of existing land-use patters from satellite images), but density profiles constrain the models to much better reflect the true urban form of the city being modeled.

Population and employment density, and accessibility profiles are calculated for Austin using data from the EPA's Smart Location Database (SLD) (Ramsey and Bell 2013). The SLD is the only nation-wide data set that characterizes attributes like housing and employment density, as well as accessibility, land use diversity, and transit coverage. SLD zones are based on Census block groups, and therefore vary in size, reflecting (to some extent) variable population densities (Ramsey and Bell 2013). To calculate land use metrics in Austin, Euclidean distance bands were created, with 1-mile radius increments, to a city center point in Austin's Central Business District (taken to be the intersection of 6th Street and Congress Avenue). All cells whose centroid locations fall within each 1-mile band were banded together.

Model city form was manipulated through trial and error until each band's density and accessibility values reflected that of the actual region, in terms of resident and worker populations. Total urban energy was then calculated as the sum of the various different neighborhood types, assuming uniform energy demand profiles and populations for each neighborhood type. These cell-based models are rather rigid in their extension to city-level analysis, and should probably depend more on large-scale measures of urban form, and thus land use patterns over space, rather than on local or neighborhood-level details. Certainly the method could be improved by models more sensitive to accessibility and aggregate city and employment values. However, this whole-cities extension of the Austin-neighborhood-focused estimates provides a rare glimpse of energy consumption sources across various residential and commercial settings and phases quickly and easily.

4.3 City-Scale Life-Cycle Energy Use Results

The following results present the model and true city density and accessibility profiles for five case study cities, along with rather comprehensive life-cycle analyses for a resident and worker perspective.

4.3.1 Synthetic City Form

After matching cells to approximate actual land use settings, and adjusting these to better conform to density and accessibility metrics, five model cities were created. Figures 4.1, 4.2, and 4.3 show results for Austin. The remaining model city results can be found in Appendix A.

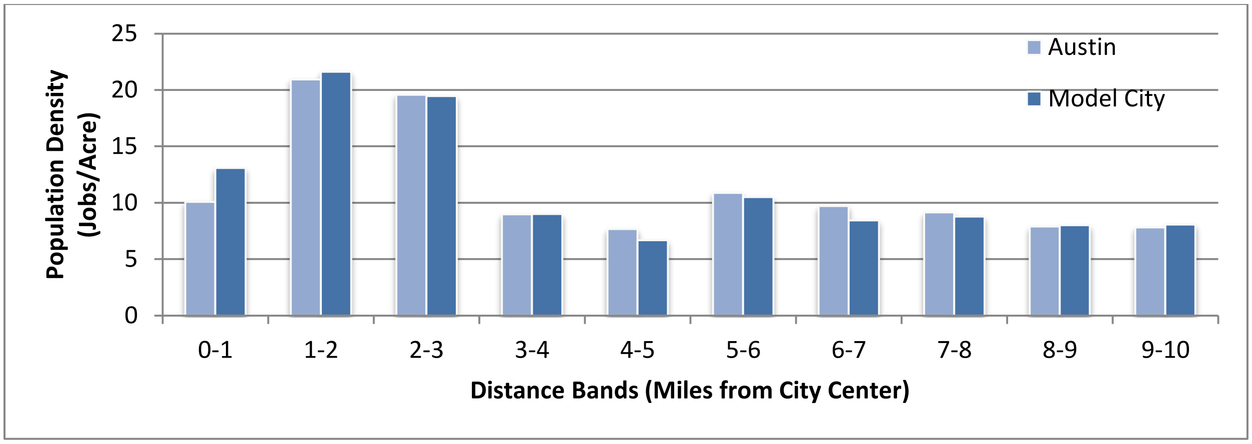

Figure 4.2: Model vs. Actual (Average) Population Density by Distance from City Center, Austin, Texas

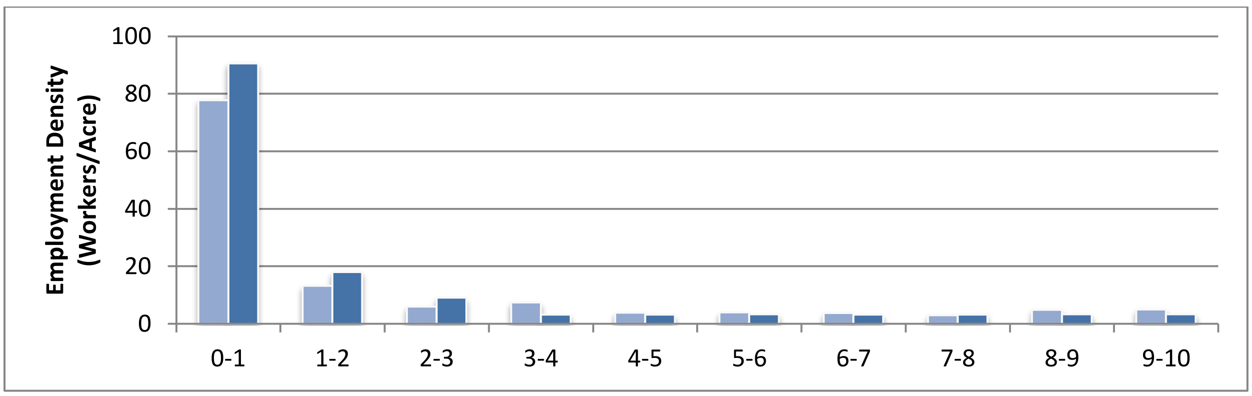

Figure 4.3: Model vs. Actual (Average) Employment Density by Distance from City Center, Austin, Texas

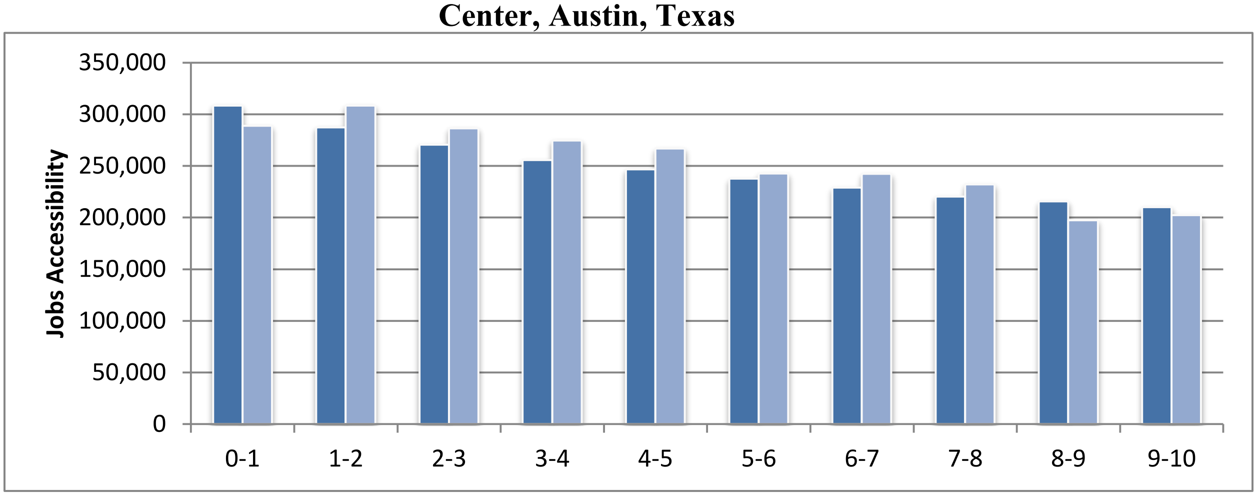

Figure 4.4: Model vs. Actual (Average) Jobs Accessibility by Distance from City Center, Austin , Texas

Figure 4.5 shows Austin's final residential and commercial neighborhood tile types. Note that commercial tiles cover only a portion of the total land area, leaving some tiles blank. This result comes from efforts to match both jobs density profiles and total regional jobs. Results for other cities can be found in the Appendix.

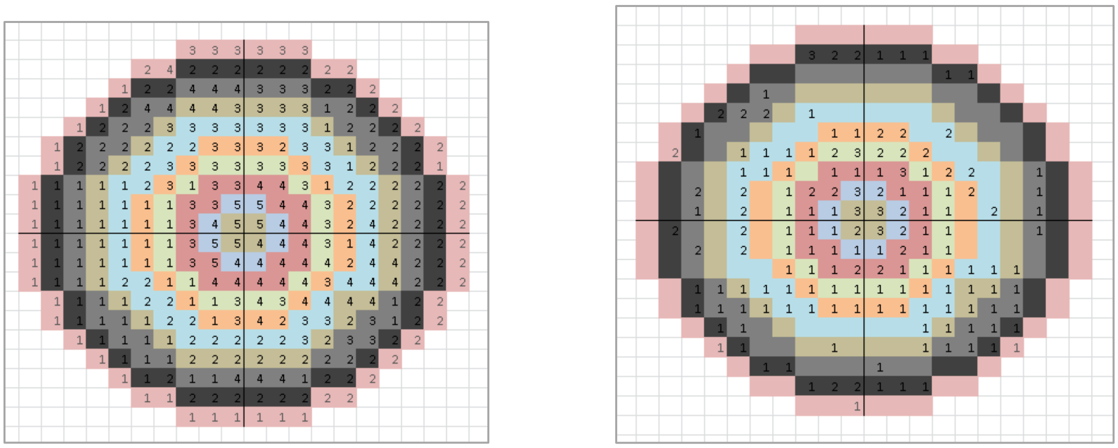

Figure 4.5: Residential (left) and Commercial (right) Land Use Patterns for the Austin, Texas Case Study

While city-specific details are found in the Appendix, summaries for each city model are found below. Table 4.1 displays the actual city parameters for average densities, population and employment, and resident-worker ratios, and life-cycle energy consumption estimates from the model. Figure 4.6 presents the same information graphically, separating energy consumption by sector and phase, across each model city.

Table 4.1: Actual City Attributes and Selected City Model Results

		Orlando, FL	Phoenix, AZ	Austin, TX	Seattle, WA	New York, NY
Actual City Parameters						
Avg. Population Density (residents/acre)		8.2	10.7	11.3	16.8	96.1
Avg. Employment Density (jobs/acre)		6.7	9.4	12.9	19.2	67.2
10-mile Radius Population		1,694,190	2,938,682	1,253,279	2,224,567	12,263,511
10-mile Radius Jobs		934,052	1,640,268	679,658	1,245,834	5,130,862
Resident-to-Worker Ratio		1.81	1.79	1.84	1.79	2.39
Model Results						
Avg. Population Density (residents/acre)		8.4	12.2	10.1	13.73	27.0
Avg. Employment Density (jobs/acre)		4.6	8.5	7.7	9.08	108.3
10-mile radius Population		1,616,601	2,388,833	1,296,611	2,109,083	5,312,704
10-mile radius employment		816,576	1,663,494	686,003	11,219,742	4,756,135
Residents-to-Jobs Ratio		1.88	1.44	1.9	1.73	1.12
City Total (PJ/year)	Operations – Resid.	147.8	180.3	97.3	154.5	323.9
	Embodied – Resid.	48.8	43.1	22.4	34.0	39.1
	Operations – C/O	25.2	45.5	19.5	33.3	125.2
	Embodied – C/O	3.7	3.3	1.9	2.3	2.2
	Total Operation	173.0	225.8	116.7	187.8	449.1
	Total Embodied	52.5	46.4	24.3	36.3	41.3
	Life-Cycle	225.5	272.2	141.0	224.1	490.3
City Average (GJ/capita/year)	Operations – Resid.	91.5	75.5	75.0	73.3	61.0
	Embodied – Resid.	30.2	18.0	17.2	16.1	7.4
	Operations – C/O	15.6	19.1	15.0	15.8	23.6
	Embodied – C/O	2.3	1.4	1.5	1.1	0.4
	Total Operation	107.1	94.5	90.0	89.1	84.5
	Total Embodied	32.5	19.4	18.7	17.2	7.8
	Life-Cycle	139.6	113.9	108.8	106.3	92.3
Operations (PJ/year)	Transport	71.0	82.1	44.5	70.3	135.3
	Buildings	100.3	141.7	71.1	115.9	310.0
	Other Infra.	1.6	2.0	1.1	1.6	3.7
Embodied (PJ/year)	Transport	19.3	18.3	9.5	14.5	19.3
	Buildings	32.4	27.3	14.3	21.1	20.5
	Other Infra.	0.7	0.9	0.5	0.7	1.4
Total (PJ/year)	Transport	90.3	100.3	54.0	84.7	154.6
	Buildings	132.7	169.0	85.4	137.0	330.6
	Other Infra.	2.4	2.9	1.6	2.4	5.2

Note: C/O designates commercial and/or office land uses.

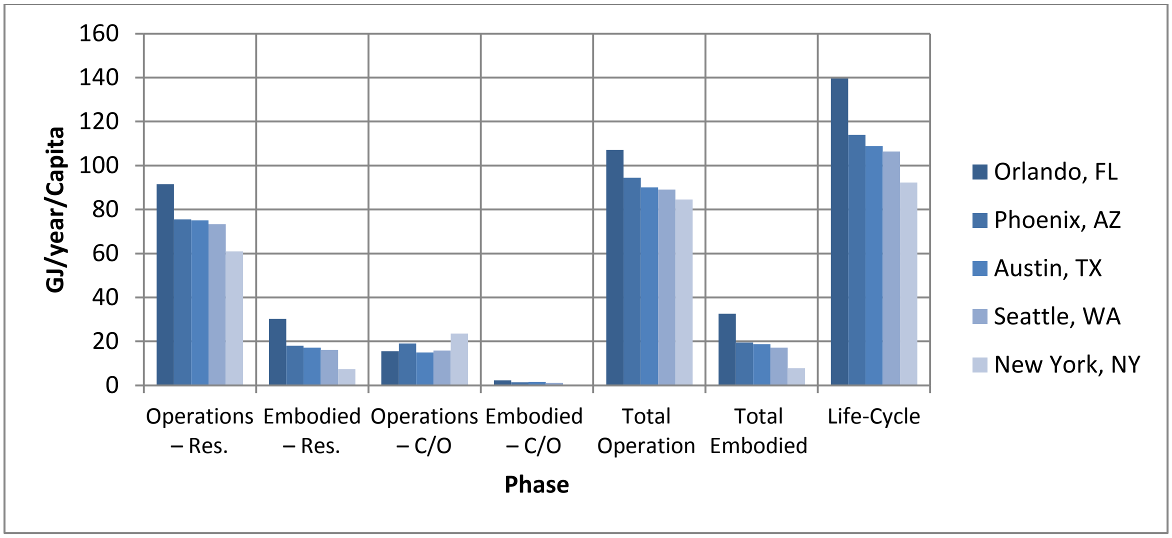

Figure 4.6: Life-Cycle Energy Use by Sector and Phase

4.4 Discussion

These model results provide a quantitative estimate of how city form influences per capita emissions rates, at an aggregate level. These findings suggest that city form, measured and by jobs accessibility, population and employment density, are likely to affect per-capita energy consumption (and emissions profiles, ceteris paribus). Additionally, those changes in energy use across different urban forms may come more substantially from the embodied energy phase) as more residents and workers share existing infrastructure with greater intensity). Model results suggest that per-capita life-cycle energy in the most dense setting (the New York setting) is only two-thirds that of the least dense (Orlando). The most notable change in life-cycle energy savings, shifting from the Orlando to New York environment, is from the embodied energy phase. Per-capita embodied energy in the New York setting is only one quarter of that in Orlando. Operations energy, meanwhile, is about 80% less per person in New York versus Orlando. (It is important to note that a more accurate New York model would likely show even greater differences in both operations and embodied energy savings, seeing as how increased neighborhood densities generally lead to fewer per-capita emissions, though it is uncertain how exactly economies of scale would apply as density increases to the comparatively large values seen in New York.)

As the least dense and most energy-intensive environment for per-capita consumption, Orlando can be used as a pivot point to compare relative energy consumption across the four other city styles, as shown in Table 4.2.

Table 4.2: Per-Capita Annual Energy Savings, Relative to Orlando Setting

% Energy Change (per capita) versus Orlando	Phoenix	Austin	Seattle	New York
Operations Phase	-11.8%	-16.0%	-16.8%	-21.1%
Embodied Phase	-40.3%	-42.5%	-47.1%	-76.0%
Total Life-Cycle	-18.4%	-22.1%	-23.9%	-33.9%

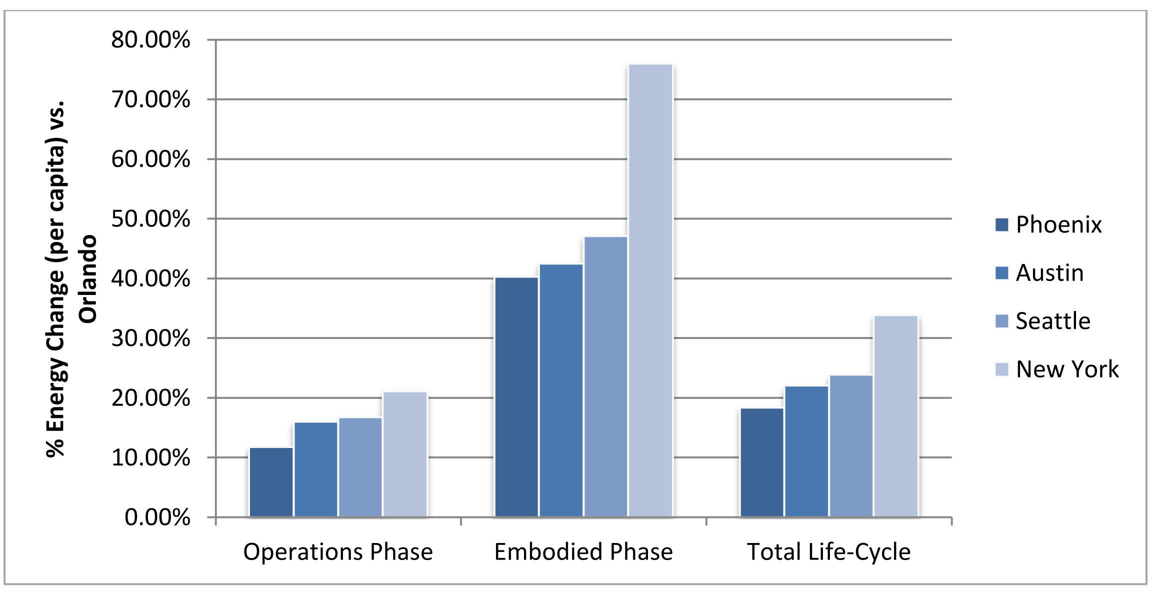

Figure 4.7: Relative Energy Savings for Cities vs. Orlando

These results indicate that built environment styles certainly vary across cityscapes, with efficiency increasing with density. This finding is clear in the operations phase, with efficiency increases between around 12 and 20%, but much more pronounced for embodied energy, with efficiency gains between 40 and 76%. Altogether, total life-cycle energy savings, when shifting from an Orlando-style setting, varies between around 20 and nearly 35%. This finding reinforces common perceptions that increasing resident and employment density reduces regional energy demand from day-to-day uses (i.e., the operations phase), but also suggests that embodied energy savings contributes additional efficiency gains. By including this often "unseen" phase of energy consumption and considering a more holistic life-cycle perspective, density and accessibility become even more important metrics for improving regional energy efficiency, and consequently reducing greenhouse gas emissions and perhaps improving local air quality.

One challenge of this task is extrapolating a rather small set of selected Austin neighborhoods to higher-density environments. For instance, the maximum-density neighborhood of Austin (around 20 residents per acre) is well below the average resident density in the New York area. For this case, the maximum density Austin neighborhoods are used, but fall well short of actual density profiles. Even though the results therefore do not reflect the actual urban design of New York, the relative focus on high-density neighborhoods still provides some context of relative energy savings. A more detailed analysis might extend the original neighborhood set to include more dense and diverse neighborhoods. As these neighborhoods are "building blocks," a standard set could be expanded for more detailed and finely tuned analyses.

CHAPTER 5 : CONCLUSIONS

This study provides rare insight into urban energy use on a large scale, and includes a holistic perspective on energy use by sector and phase. It extends the concept of life-cycle analysis to a very aggregate level and then compares rather extreme city patterns in the U.S. To the author's knowledge, there are no other models that have attempted to quantify total life-cycle energy for a city at the scale of this work. Such results provide a context for evaluating the relative impact of energy savings schemes in various sectors and allow a more quantitative comparison of energy efficiency across different urban environments.

These results suggest that city form is very important for considering energy efficiency and associated emissions. If these findings are indeed accurately capturing energy differences across different urban settings, the implications become rather apparent when extrapolated to a national or global setting. Consider first, anticipated growth in the U.S. by 2050 to be around 125 million, to a total population of 440 million. In the year 2050, if these 125 million new residents are living in a setting similar to that of Orlando, (and assuming, for simplicity that energy efficiency remains constant over time) they will consume around 17,500 petajoules (16.5 quads) of energy per year. Meanwhile, if that population were in an environment similar to New York, they may require only 11,500 petajoules (nearly 11 quads). The difference between those two extreme scenarios is 5.5 quads of energy, which a little less than half of all energy consumed by the residential sector today, or about 6% of the U.S.'s current aggregate energy consumption.

Extending this analysis to a global scale is challenging, since New-York-style densities are far surpassed by cities like Manila and Delhi, and even greater per-capita gains are likely achieved from such dense settings. However, as a thought exercise, consider a 1.8 billion global population growth by 2050 (up to 8.9 billion from 7.1). In reality, few of these new residents would be consuming anywhere near the levels of citizens in the U.S., but consider that they are. (It is not entirely unrealistic to expect an increase in high-consumption populations with increased wealth in growing countries.) In an Orlando setting, this marginal population would require 251,000 petajoules (237 quads), versus 166,000 petajoules (157 quads) for a New York setting. The net difference is 85,000 petajoules, or 80 quads, equal to 84% of today's entire energy consumption in the United States. Perhaps the most startling idea from this exercise is the fact that even in the relatively efficient environment, (e.g., New York) total energy demand from a marginal global increase of nearly 2 billion people would require an additional energy supply 1.6 times the current U.S. rate.

Of course, these thought exercises are over-simplifications, but they help to understand just how important urban energy efficiency will be in the coming decades. This study points out that growing energy demands can be dampened to some degree by building cities with continued focus on infill and compact development, to promote density and reduce per capita life-cycle energy demands. Including a holistic perspective beyond the day-to-day energy demands allows one to quantify the efficiency gains of more intensively using public infrastructure and building stock, leading to less energy demand, fewer emissions, and likely less cost. Density is often touted as a means to achieving efficiency, and this study bolsters that call by providing an additional dimension of analysis to understand energy demands more holistically. In many cases, when density is considered to reduce daily energy demands by a given amount, it is very likely that embodied energy savings would only amplify that value and bring even greater efficiency gains into the equation.

PART II: PLUG-IN ELECTRIC VEHICLES

The first part of this thesis quantified to what extend that urban life-cycle energy and emissions are tied to both buildings and personal transportation. Efficiency improvements and demand management emerge as important focus areas for policy and design. Both fields have received serious research attention and have been supported by various policy approaches. Related to this, low-energy LEED-certified buildings have been growing in demand since their introduction in the early 2000s (Turner and Frankel 2008), and energy-efficient hybrid electric vehicle (HEV) market shares have been growing steadily since around the same time (Diamond 2009). These trends have been prompted by a mix of consumer interest in reduced costs from improved efficiency and/or environmental consciousness, technological development, and policy incentives that support energy-savings products and practices.

The second part of this thesis focuses on the emission impacts of plug-in electric vehicles (PEVs) in Texas. PEVs represent a fundamental shift in the way transportation energy is consumed and emissions are distributed. Over the past few years, improvements in EV technology, infrastructure, and vehicle alternatives have drawn interest towards their impacts on power grids, air quality, climate change, vehicle-miles traveled, road safety, and more. This work develops modeling techniques and case studies to anticipate emissions impacts across Texas. The following chapters explore some of these analytical approaches and develop a basis for evaluating EVs' role in the future of transportation.

CHAPTER 6 : BACKGROUND

Plug-in electric vehicles (PEVs) are becoming more popular in the United States and around the world. As of early 2013, the U.S. held an estimated 70,000 PEVs, nearly 40% of the world's total of over 180,000 (IEA 2013). Since PEVs were reintroduced more strongly into the passenger vehicle market in the early 21st century, researchers and policy makers have been considering the short- and long-term impacts of PEVs on energy, electricity, and transportation infrastructure, and the environment. Much of the discussion includes uncertainty regarding consumer adoption and technological development of vehicles and energy infrastructure and whether or not PEVs can reduce the externalities of driving. Despite these uncertainties, many believe that PEV market shares will continue growing in the next few decades (Balducci 2008, Musti and Kockelman 2011, Becker and Sidhu 2009) and that this trend, in most cases, will reduce greenhouse gas (GHG) emissions (Anair and Mahmassani 2012, Stephan and Sullivan 2008, Samaras and Meisterling 2008) and improve air quality (Sioshansi and Denholm 2009, Thompson et al. 2009).

Even as many adopt an optimistic tone towards PEVs, others cite some concerns. Anair and Mahmassani (2012), for instance, note that PEVs can pollute more than some of the cleanest conventional vehicles (CVs) when fueled by "dirtier" electricity grids (powered mostly by coal). They suggest that in such locations (e.g., Colorado and the U.S.'s Midwest) driving an efficient (gasoline-powered) hybrid-electric vehicle would actually be less harmful (in terms of GHG emissions). However, they did note that places the Pacific Northwest, which sources a large portion of electricity from non-emitting hydroelectric dams, enjoys very low per-mile GHG emissions relative to CVs.

Another concern with PEVs is the energy demands and unique pollution required for battery production (and disposal) and the higher energy required to produce lighter-weight materials (Hawkins et al. 2012), as well as potential driving rebound due to reductions in costs and perceived environmental impacts, causing some owners to increase their driving distances.

Such limitations are also seen in the context of an increasingly clean CV landscape, diminishing PEVs' environmental and efficiency benefits. Vehicles powered by fossil fuels produce are producing fewer emissions and becoming more fuel efficient, thanks to increasingly strict standards. Understanding and predicting these trends is anticipating the transportation sector's energy demands, air quality impacts, and greenhouse gas emissions. While much has been written on this subject, uncertainty remains regarding how electric vehicles impact specific markets and regions.

6.1: Electricity Generation In Texas

As pointed out by Anair and Mahmassani (2012), PEV impacts depend on the power grid used to charge vehicle batteries. Texas is served by an isolated grid that covers nearly 90% of the state population, and serves as an excellent study location, since regional demand can be directly linked to a single grid (as opposed to other, interconnected grids that distribute power across multiple independent system operators (ISOs). The Electric Reliability Corporation of Texas (ERCOT), one of the U.S.'s nine ISOs for electricity grids in the U.S., managed the Texas grid by dispatching power and anticipating short- and long-term electricity demands. 195 Texas's 253 counties lie within the ERCOT grid, which includes major metropolitan areas of Dallas-Fort Worth, Houston, San Antonio, and Austin, which are the nation's the 4th, 5th, 25th, and 35th most populous metropolitan statistical areas (MSAs) in the U.S. (Census 2010). Table 6.1 describes the ERCOT coverage area and Figure 6.1 indicates geographic distribution of EGUs (by fuel type) across the ERCOT grid.

Table 6.1: ERCOT Grid Characteristics

	ERCOT Grid Counties
Area	212,571 (mi^2)
% Texas Land Area[9]	79.0%
2010 Census Population	22.3 million
% Total Texas Population[10]	88.8%
EGUs	550
Transmission Line Miles	40,453

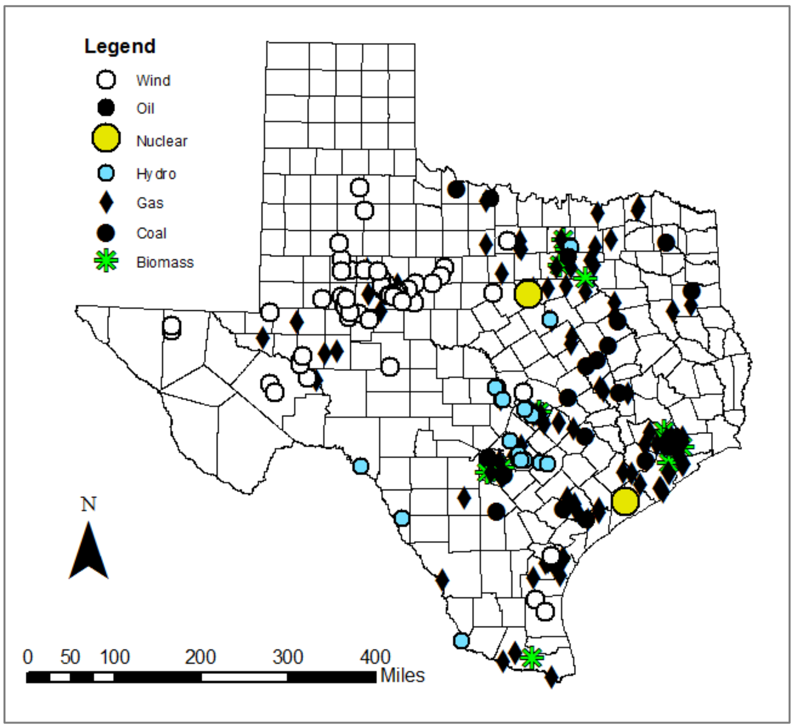

Figure 6.1: ERCOT EGU Location by Fuel Type

[9] Total land area of Texas measured to be 268,943 mi^2 in GIS analysis.
[10] Total 2010 population of Texas taken to be 25,145,561.

ERCOT (2012) expects peak demand to increase around 45% over the next 20 years (by 2033), growing to over 96,000 MW from the current peak of nearly 67,000 MW. However, ERCOT (2012) anticipates fuel type shares to remain relatively constant across the next ten years, with the predicted coal shares decreasing nearly 2% (from 25.5% of total generation in 2013 to 23.7% in 2022) and gas share increasing nearly 1% (from 64.1%. in 2013 to 65.0% in 2022). This forecast is more static than nationwide forecasts, which anticipate a 6% drop in coal shares (from 45% of total generation in 2010 to 39% in 2020) and a 1.5% increase in natural gas shares (from 24% in 2010 to around 26.5% in 2020) (EIA 2012). Given these rather minor shifts in power feed stocks the fuel share mix is assumed constant in this analysis. However, even with a consistent mix, emissions rates may change as older, less efficient plants are decommissioned and newer facilities (of the same fuel type) replace them. An analysis of emissions rates as a function of construction date (first year the EGU was online) from eGRID shows weak trends, suggesting that many older ECOT plants may have been retrofitted, and/or not all new plants are built to a low-emissions standard. Figure 6.2 shows the strongest correlation found between eGRID emissions and generator start date, for NO_x emissions rates across natural gas plants.

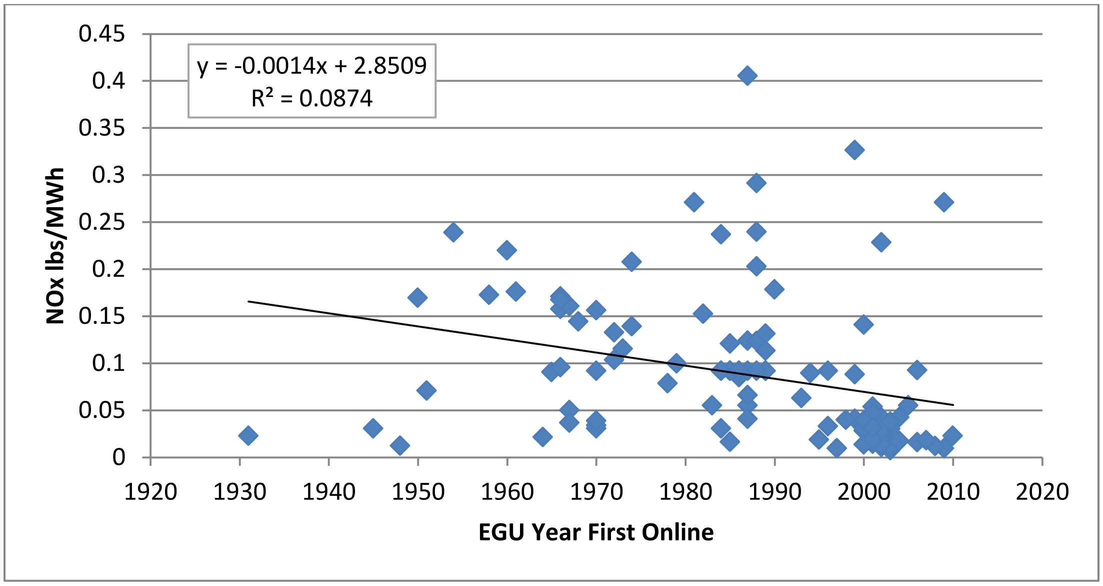

Figure 6.2: NO_x Emissions Rates for ERCOT Natural Gas Plants by Build Date

This analysis shows a large cluster of newer plants, built between 2000 and 2010, with consistently low emissions rate (at or below 0.05 lbs of NOx per MWh). However, a set of outliers across all years reduces the certainty of a linear trend, with new plants emitting over 0.3 lbs/MWh, and the oldest natural gas generator (onlinearound 1930) emitting as much as the newest plants.

The ERCOT grid now functions as a nodal market, rather than a more traditional zonal market, meaning that power can be distributed more evenly across the entire grid, rather than shifted across geographic zones. This distinction mostly refers to how electricity pricing is managed, but the shift was implemented to reduce transmission line congestion and prompt new EGU construction along less congested transmission lines (Dyer 2011). This market structure impacts PEV emissions analysis, since electricity consumed at any point on the ERCOT grid can come from any generation facility on the grid. In other words, this structure removes any geographical constraints between electricity producers and consumers, and emphasizes providers can produce electricity at the lowest marginal cost. This makes it very difficult to relate PEV charging demand to point-source emissions locations, without incorporating an economic dispatch model.

6.2: Emissions and Air Quality

One criticism of PEVs is that they are not "zero emissions" vehicles and produce significant emissions during manufacture, and shift operating emissions from the tailpipe to other locations. Some have argued that PEVs can be worse for the environment, by producing more life-cycle GHG emissions, though the impacts may be obscured by geographical distance and the fact that many impacts occur during upstream production phases (Hawkins et al. 2012, National Research Council 2010, Alonso et al. 2012). Regardless of how overall PEV energy demands compare to CVs, it is true that PEVs shift emissions from the point of usage (a roadway) to a sometimes very distant point source. PEV users and others in the usage area therefore benefit from zero tailpipe emissions, while populations surrounding the power source may be subject to more air pollution. That accounting framework becomes more complicated when plug-in hybrid electric vehicles (PHEVs) are included in the mix, since their emissions shift between battery and gasoline sources. The emissions shifting situation presents ethical dilemmas and may encourage more driving, by reducing users' perceptions of impacts (Hertwich 2008). However, reducing exposure of highly populated urban areas may be a real benefit of such emissions "exporting."

One approach to addressing this problem is to view emissions objectively, by considering population exposures from power plants producing PEVs' electricity. This is rather challenging to model with certainty, since individual plant generation fluctuates, but it is possible to consider average emissions rates, based on past usage, and to analyze affected populations within a certain range. Defining a range of exposure is also difficult, though, since health and other impacts vary by pollutant type, weather, micro-climates, and individuals' health, behavior, and outdoor exposure. This study will leave such details to air quality modelers and epidemiologists, and will evaluate aggregate emissions exposure rates, taken as the product of annual EGU emissions and surrounding county population.

Some of the most harmful byproducts from both vehicles and power plants are particulate matter, carbon monoxide, and nitrogen oxides. In the U.S., all vehicles (cars, trucks, buses and off-road vehicles) produce over half of anthropogenically-derived smog-forming volatile organic compounds (VOCs), nitrogen oxides (NOx), and around three-quarters of total carbon monoxide (CO) emissions (EPA 2012b). These pollutants damage health on their own, or react to produce ozone, acid rain or other secondary pollutants. Direct inhalation of CO reduces blood's ability to carry oxygen to vital organs, and may cause most significant to young children and those with pre-existing heart disease (EPA 1994). Particulate matter (PM) also causes direct harm to humans at high concentrations and exposure rates. PM primarily affects the respiratory system, causing asthma, bronchitis, chronic obstructive pulmonary disease, pneumonia, and upper respiratory tract infections (Buckeridhe et al. 2002).

Air quality became a major concern around the mid-20th century, as more automobiles packed the roadways and cities grew to accommodate the rising populations, along with the new mode (Bachmann 2007). In 1970 the U.S. introduced the Clean Air Act, which set standards for automobile emissions rates, and developed acceptable urban toxin levels for key health-impacting pollutants. These efforts have been mostly successful as of the early 21st Century; nearly all of the U.S. falls within original air quality targets for CO, NOx, and SO_2. The EPA (2011) maintains that modern light-eduty vehicles (LDVs) and heavy trucks are up to 95% cleaner than models before emissions regulations, and over 26,000 premature deaths, 19,000 hospitalizations, and 3.2 million lost work days have been avoided as a result of actions taken to meet Clean Air Act requirements. Between 1990 and 2008, VOC, CO, and SO_2 emissions were reduced 31, 46, and 51 percent, respectively (EPA 2011). Ambient air concentrations of lead, which can cause mental disorders in children at high concentrations, have fallen 92% since 1980 (EPA 2011).

Many U.S. regions are interested in improving air quality to avoid violating the EPA's National Ambient Air Quality Standards (NAAQS). With many Texas regions currently in non-attainment or near-non-attainment for ozone, while experiences continuing population and VMT growth, PEVs present an opportunity for improved air quality and lower energy demands. However, it is unclear just how much of a benefit PEVs might have for specific locations, and whether shifting from on-road to point-source (power plant) emissions will result in significant net benefits. Additionally, there are concerns that large-scale shifts towards PEVs may be inequitable for those residing and working near power generation sources. These impacts are examined over space and time in detail in this study. This paper develops PEV emissions rates for GHG and pollutants to understand how PEV adoption and electricity generation scenarios may impact Texas's urban air quality.

This work involves different model components, which can be separated into vehicle usage, electricity production, and emissions. The first part considers how readily PEVs may be adopted, how they will be used, and their electricity demand over time. Power production and emissions estimates depend on feed stocks used, over time and space, and requires extensive model development. The following chapter focuses on PEV adoption, use and charging patterns around Texas and creates a model for capturing dynamic emissions profiles across the state.

CHAPTER 7 : ANTICIPATING PEV ADOPTION AND USE

This research translates anticipated PEV demand to emissions over time and space within Texas's electric grid. The emissions impacts are evaluated relative to conventional (gasoline-powered) passenger vehicles, and in terms of the marginal impact of adding electrified miles to a fleet of conventional vehicles (CVs).

7.1 ELECTRIC VEHICLE OWNERSHIP MODEL

Although plug (PEVs are the subject of extensive research, very little PEV ownership and usage data is made publicly available. State vehicle registries do try to count EVs and include vehicle location and owner information, but this data is rarely released for research (or is provided at a cost). Some private databases do exist, but PEVs are such a new vehicle class that no large surveys (such as the National Household Travel Survey [NHTS]) include sufficient sample sizes. The most recent version of the NHTS dates to 2009, and includes only 15 total PEVs, out of 309,163 total vehicles (NHTS 2009). In many cases BEV ownership data is unavailable due to such small sample sizes and confidentiality concerns for owners, as well as vehicle identification numbers (or VINs) that can change yearly for specific makes, models and styles of vehicles, hindering states' EV accounting and any related research.

In light of such data challenges, Texans' BEV ownership is anticipated here as a function of HEV ownership, which is generally easier to determine with higher statistical significance, since many more HEVs than PEVs already exist in the U.S. PEVs and HEVs are very different in terms of ownership levels and potentially usage levels (with HEVs having no range limitations and being highly valued for long-distance trip-making, for example), but some assumptions of "early adopters" may be relevant and useful to proxy for PEV ownership at a neighborhood level. Though PEVs and HEVs vary in the way they are priced and can be fueled, much of the same ownership appeal may be shared by prospective PEV and HEV owners. For instance, both HEVs and PEVs can appeal to individuals interested in reducing travel costs by reducing energy costs (Khan and Kockelman 2012, Tuttle and Kockelman 2012). PEV and HEV owners are often more concerned with the environmental impacts of CVs, and/or simply more interested in being the first to experience a new vehicle technology. For HEV owners concerned about range limitations, PHEVs like the Chevrolet Volt and Toyota plug-in Prius make great sense, while a Nissan Leaf or Ford Focus (both BEVs with under 100 miles all-electric range [AER]) may not.

Understanding how HEV demand translates to BEV is rather complicated, but this study will avoid many generalizations in ownership behaviors by simply assuming that EV ownership is an aggregate share of total HEVs. For instance, U.S. data suggest that PEVs currently make up about 0.05% of all light-duty vehicles owned by Americans, while HEVs make up 1.4%[11].

Two negative binomial models are estimated for HEV and total passenger vehicle counts (per block group) vehicle registration data from the Philadelphia, Pennsylvania metro area. This data was combined with the EPA's Smart Location Database (SLD) to include more demographic and built environment variables. The HEV data, as used by Chen et al. (2013) and originally provided by the Delaware Valley Regional Planning Council (DVRPC), counts total registered EVs (and total registered passenger vehicles) per Census block group (as of April 2012), where the term "EV" includes all HEVs, BEVs, and PHEVs, as best they could be distinguished by VINs. (Note that EVs are

[11] As of April 2013, the U.S. had around 71,000 passenger EVs on the road, which includes BEVs, PHEVs, and fuel cell electric vehicles (IEA 2013) and nearly 3 million HEV sales since 2000. This assumes that all vehicles sold are still on the road. Data sourced from HybridCars.com

distinct from PEVs, as defined previously). It also distinguishes the popular Toyota Prius modeled from other EVs. Given these count data, a negative binomial regression model was estimated to anticipate both total EV counts and Prius counts. However, to provide more demographic and unique spatial variables into the model, the DVRPC data is joined with the SLD. The SLD contains many land-use and demographic characteristics for block groups across the U.S., and provides a richer model estimate for EV distribution in the DVRPC data. The SLD data contain some information on auto ownership shares by count (based on American Community Survey data), but results reflect only the zero, one, and "two or more" vehicle-ownership categories. Therefore, households with three or more cars are not fully accounted for. However, this number provides at least a lower bound estimate for vehicles across the study area, at 13,520,485 vehicles. Results from the SLD data indicate that 1.51 vehicles were owned per household on average, with a standard deviation of 0.275 across block groups. The DVRPC data indicate an average of only 1.39 vehicles per household with a standard deviation of 0.532. The discrepancy in household vehicle counts between the two datasets may arise from the way vehicles are counted for the SLD (such that all owned vehicles are not necessarily registered at that household's address).

The joined data were fit using two negative binomial models: one for total vehicle count per block group and the other for total EV counts by block group, as a function of block group population, working age population share, number of medium and high wage workers, population and employment densities, and accessibility (as measured by the SLD). Table 7.2 and 7.3 show their model results.

Table 7.1: Negative Binomial Model for Total Vehicle Counts per Block Group

Parameter	Coefficient	Std. Error	Significance
Intercept	6.611	0.0500	0.000
Population Density (per acre)	-0.014	0.0008	0.000
Employment Density (jobs/acre)	0.001	0.0006	0.033
No. of workers earning between $1,250 and $3,333 per month	0.001	0.002	0.000
Likelihood ratio chi-square	356.11		

Table 7.2: Negative Binomial Model for EV Counts per Block Group

Parameter	Coefficient	Std. Error	Significance
Intercept	1.6737	0.2246	0.000
Total block group population	-0.0001	5.356E-05	0.022
Proportion of Population of Working Age	1.3899	0.2762	0.000
No. of workers earning between $1,250 and $3,333 per month	-1.91E-03	0.0004	0.000
No. of workers earning more than $3,333 per month	1.93E-03	0.0002	0.000
Population density (per acre)	-1.30E-03	0.0015	0.000
Employment density (jobs/acre)	0.0010	7.0E-04	0.142
Accessibility – jobs with 45 minutes auto travel time	1.0E-05	1.19E-06	0.000
Accessibility – working age pop. within 45 min. auto travel time	-9.0E-06	-1.04E-05	0.000
Likelihood ratio chi-square	356.108		

These two models' parameter sets were are applied to the ERCOT study area's block groups (from the SLD), with summary results shown in Table 7.4.

Table 7.3: Negative Binomial Model Estimates for EV and Total Vehicle Ownership Counts across ERCOT Block Groups

	Average Prediction	Min Prediction	Max Prediction	Total Prediction
Passenger Vehicles per Block Group	955	1	39,383	13,081,076
Passenger Vehicles per Capita	0.897	0.001	373	--
Passenger Vehicles per Household	2.93	0.002	1168	--
HEVs per Block Group	10.7	0	2695	146,425
HEV Shares (of all Passenger Vehs.)	0.0033	0.0001	1	--
HEVs per Capita	0.000	0.000	0.5	--
HEVs per Household	0.628	0	1257	--

These results return a more reasonable split between total vehicles and HEVs, and also come reasonably close to matching actual registration data in the ERCOT counties (as detailed in the following section). A total of 146,425 HEVs anticipated in the study zone makes up about 1.1% of total passenger vehicle registrations, on par with the 1.4% national shares. Assuming the same (national) proportions between HEVs and EVs would then suggest that the ERCOT region contains around 6,540 PEVs. Though these models appear rather useful for predicting HEVs and total vehicles, it may be unwise to depend on such an arbitrary extrapolation to derive actual EV ownership. The following sections describe an alternate approach to anticipating EV ownership.

7.2 Direct EV Adoption Scenarios

Another approach for anticipating PEV emissions impacts is to define a set of hypothetical adoption scenarios. Since emissions are considered across the entire ERCOT power grid (i.e., any power plant may provide the power to charge a PEV), the actual ownership distribution of PEVs is irrelevant (unless PEVs were to replace CVs, in which case some localized air quality analyses could be considered).While it may have been necessary to model PEVs' charging locations in the past, the ERCOT grid now functions as a nodal market, rather than a more traditional zonal market. This means that power can be distributed evenly across the entire grid, such that an EV in south Texas may be drawing power from an EGU hundreds of miles away at Texas's northern border. This system is complicated to model at a fine scale (where each EGU's emissions are pinpointed by the exact hour of the year, for instance), but it does simplify the process of electricity demand from PEVs into a more aggregate approach.

Thanks to this simplification, and some uncertainty in the ownership model predictions, this study considers a few hypothetical PEV ownership scenarios for the subsequent analyses and discussion. PEV shares of 1%, 5%, 10%, and 25% of all light-duty passenger vehicles are evaluated here, at 10-year increments up to 2050. While it is uncertain that the higher-end of these shares will be reached, these scenarios present a likely lower and upper bound of possibilities, at least for the near term. Becker and Sidhu (2009), for instance, note that even if general EVs grow to 64% of total U.S. passenger vehicle sales by 2030, they would only make up about a quarter of all the nation's passenger vehicles at that point. This estimate is also exclusive to general EVs; PEVs are likely to make up an even smaller share.

From these shares, the total number of EVs can be estimated from vehicle-registration data at the county level. The Texas Department of Motor Vehicles provides counts of registered light-duty vehicles (LDVs) and total vehicles (including fleet vehicles and trucks) for as recent as 2009, and total vehicle registrations up to 2012. LDV counts are not available for 2012, but were estimated here by multiplying 2009 shares, for each county, by 2012 total vehicle registrations. Only counties within the ERCOT region were selected for this analysis, to represent vehicles that are likely charging at locations on the

ERCOT grid. Table 7.4 reports registration totals for all Texas counties and the ERCOT study region, by vehicle type and year. It is assumed that the shares of LDVs remain constant from 2009 to 2012. Population data is provided by Texas Department of State Health Services (TDSHS 2009).

Table 7.4: Vehicle Registration across ERCOT Counties

	All Texas Counties		ERCOT Study Region	
	2009	**2012**	**2009**	**2012**
Total Vehicle Registrations	21,432,323	22,768,989	18,883,629	20,117,012
Light Duty Vehicles	16,476,921	17,512,296	14,623,814	15,581,975
Average % LDV	64.9%	64.9%	64.9%	64.9%
Population	24,782,302	26,403,743	21,845,465	23,360,309
LDVs/capita[12]	0.66	0.62	0.67	0.63

Long-term population projections up to 2050 use data from the Texas State Data Center (TSDC). (The "0.5 scenario" is selected as the population growth situation for each county, which represents net migration at one-half of the rate between 2000 and 2010. The TSDC recommends this scenario since not all counties are expected to experience growth as high as seen during that decade.) For these projections, it is assumed that the ratio of LDVs/capita remains constant. Table 7.6 reports the results of these projections for 5 time periods, within the ERCOT counties.

Table 7.5: LDV and BEV Projections in ERCOT Counties, up to 2050

	2012	**2020**	**2030**	**2040**	**2050**
Population	23,360,309	25,594,922	29,270,708	33,059,023	37,034,929
LDVs	15,581,975	15,993,637	18,213,742	20,484,329	22,861,311
1% of LDVs as EVs	155,820	159,936	182,137	204,843	228,613
5% of LDVs as EVs	779,099	799,682	910,687	1,024,216	1,143,066
10% of LDVs as EVs	1,558,197	1,599,364	1,821,374	2,048,433	2,286,131

[12] Population weighted average across counties.

25% of LDVs as EVs	3,895,494	3,998,409	4,553,436	5,121,082	5,715,328

With these estimates, a few scenarios can be considered that vary BEV penetration at different times. For instance, BEVs may remain 1% of all vehicles up until 2020, and reach 5% by 2030. From here, the shares may remain constant, or increase to 10% or higher. Alternatively, strong adoption scenarios can be tested that show 10% penetration at 2030, climbing to 25% by 2050. Linear interpolation can provide EV ownership estimated year by year in the ERCOT area.

7.3 EV Usage and Driving Behavior

With an estimate for total PEV ownership across the ERCOT grid, the next step is to estimate energy consumption of those vehicles, based on usage and driving behaviors, and therefore electricity demand via PEV charging. EVs may be used differently from conventional vehicles, thanks mostly to BEV range limitations (see, e.g., Khan and Kockelman 2012, Kang and Recker 2009). Also, the driving behavior (or drive cycle) of EVs are rather distinctive. Karabasoglu and Michalek (2012) note that BEV driving cycles affect energy consumption in a manner rather opposite that of conventional vehicles. Specifically, they suggest that BEVs consume much less energy in high congestion, city driving, versus CVs, but actually consume slightly more energy than CVs during constant highway driving.

Though these distinctions are meaningful to consider, especially when evaluating the benefits of BEVs on a transportation network, this study applies at a rather aggregate level, and so relies on average estimates for PEV owner behaviors. Specifically, EV use is based on extensive GPS data of Chevrolet Volt and Nissan Leaf owners across the United States, from the EV Project (2013). The EV Project is a joint study between research groups at the U.S. Department of Energy and Idaho National Laboratory, and industry supporters at Nissan, Chevrolet, and Ecotality (an EV Supply Equipment provider), and other various agency and industry partners. The EV Project releases quarterly summary data for vehicle electricity demand and miles traveled, for several locations across the U.S., including two Texas cities, Dallas and Houston. However, sample sizes are rather small for these two cities, especially for the BEV Nissan Leaf, such that the data are not always provided (out of privacy concerns for owners). Therefore, U.S. averages for driving distances between charges, and electricity use rates (Wh/mile) were used here. This analysis uses an average of charging behaviors over all quarters of the year in which EV Project data were collected, ranging from Quarter 1 (Q1) in 2012 to Quarter 2 (Q2) in 2013.[13] Table 7.7 reports these averages for values in the emissions model.

Table 7.6: EV Project Empirical Averages for EV Usage

	BEV (Nissan Leaf)	PHEV (Chevrolet Volt)
Avg. Daily Distance Traveled[14]	29.73 mi	39.7 mi
Avg. Distance between Charge Events	27.05 mi	27.2 mi
Efficiency	--	245.0 (Wh/mi)
Gasoline Fuel Economy	--	35.5 mi/gal
% Total Distance in ERM	--	26.5%

CHAPTER 8 : ELECTRIC VEHICLE EMISSIONS MODEL

This chapter discusses the process of translating PEV behaviors and assumptions from Chapter 7 into emissions estimates from Texas's main electricity grid. This approach reflects demand and emissions variations at the 15-minute interval, but is only useful for understanding emissions inventories at an aggregate level, since the model does not yet

[13] Quarters are defined as follows: Q1 January to March, Q2 April to June, Q3 July to September, Q4 October to December.

[14] Average distance considers only distance traveled only on days traveled.

identify the spatial distribution of (point source) emissions from power plants. Some discussion on life-cycle emissions is also presented later in the chapter, to provide a more holistic approach to BEV emissions estimation.

8.1 Translating EV Emissions to Electricity Generation Emissions

Combining usage estimates with total vehicle assumptions produces total daily electricity demand (by multiplying average daily distance traveled by efficiency). This calculation requires an estimate for BEV and PHEV shares, to determine electrified miles versus extended range mode (ERM) miles. This study examines different BEV and PHEV shares, from 0% BEV to 100% BEV shares (within the EV class) at 25% increments. Average daily electricity demand from BEVs (D) is calculated as follows:

$$D_{i,j} = ((\eta \times \alpha_{BEV} \times d_{BEV}) + (\eta \times (1-\alpha_{BEV}) \times d_{PHEV} \times (1-\beta)) \times m_{i,j}$$

where η is BEV efficiency (in miles/Wh), d_{BEV} and d_{PHEV} are average daily miles traveled by each BEV and PHEV, respectively, α_{BEV} is the share of EVs that are BEVs, β is the average percentage of daily distance PHEVs drive in ERM (often referred to as the "utility factor", and estimated to be quite high by Khan and Kockelman [2012]), and m is the total number of EVs in the study area, in year i and under adoption scenario j . Note that all these values are constant across i and j, except for the number of EVs or $m_{i,j}$.

Average daily electricity demand ($D_{i,j}$) provides an baseline for estimating aggregate load on the ERCOT electricity system, but determining generating emissions requires more nuance. For instance, the time-of-day at which a BEV draws power influences the overall emissions profile for that marginal electricity consumption, since demand profiles for electricity change over time as residents, businesses, and industry use electricity for different purposes, and in response to diurnal weather conditions. Similarly, electricity demand is affected by season, as heating and cooling demands vary. Therefore, the time of-day at which EVs are charging is important for anticipating upstream generator emissions.

The EV Project (2013) publishes quarter-hour charging profiles, which were matched to grid generation shares. Quarterly averages of total AC demand in kWh from the EV Project were normalized by the maximum demand during the quarter, to produce standard demand profiles that can applied to any level of electricity demand. For example, if the maximum electricity demanded from BEVs during a 15-minute interval is 0.0475 kWh at 7 PM, all other interval demands were divided by the sum of demand across all intervals, to produce a trend of relative demand, with a peak of 1 at 7 PM.

The EV Project data considers weekday and weekend charging behaviors, so those two empirical charging profiles were considered. Additionally, two theoretical charging behaviors were explored – a concentrated peak demand, and an off-peak demand. The concentrated peak demand is considered a "convenience" charge, in an approach borrowed from Thompson et al. (2011) that represents all EVs starting to charge right after returning home from work (or other activities), at 5pm, when electricity demand is generally peaking (due to households and business being "on" at the same time, and Texas homes cooling down during an especially hot time of day during the summer months). This approach condenses all EV electricity demand into a span of 7 hours, from 5 pm to 12 am. Conversely, an off-peak (nighttime) profile was chosen in a way to reduce emissions, by taking advantage of higher renewable (wind) shares, and fewer peak plant emissions in the late night and early morning hours. These profiles are normalized as well, so that total electricity demand is constant across each interval, during the charging period. Figure 8.1 shows the four different (normalized) charging profiles.

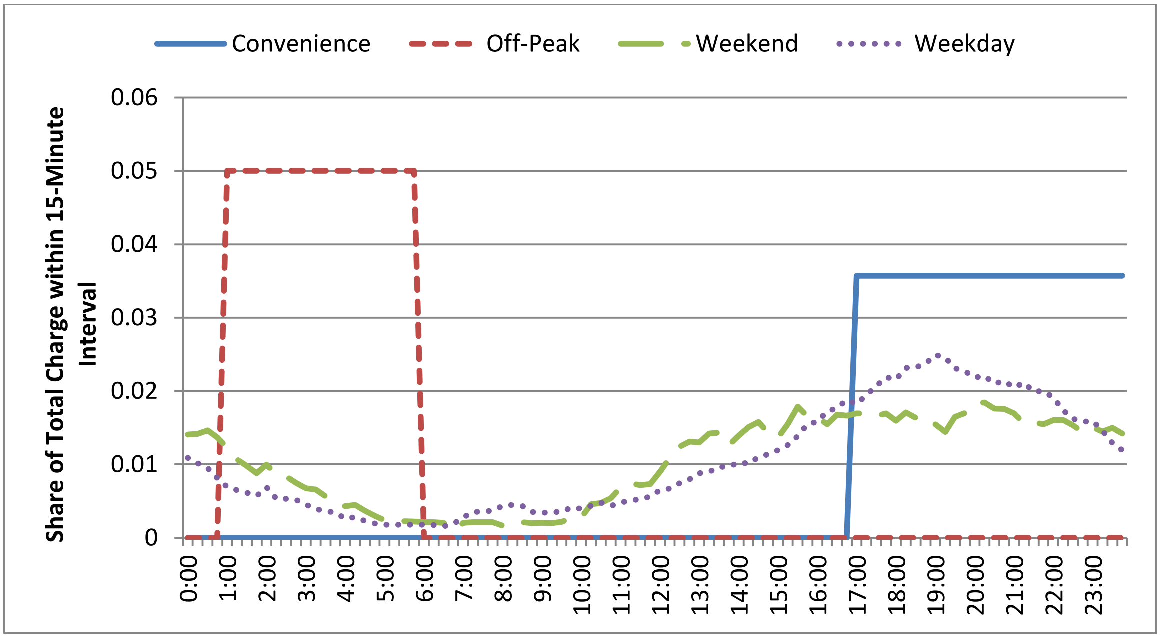

Figure 8.1: Normalized Charging Profile

The energy *E* consumed from an EV fleet charging on ERCOT's grid for a 15-minute time interval *t* is calculated as follows:

$$E_t = D_{i,j} \times \frac{d_t}{\sum_t d_t}$$

where d_t is the average electricity demand in time-interval *t,* using EV Project estimates. With this specification, total EV energy demands are spread out across 15-minute intervals concurrent with actual average profiles. EV Project data provides multiple quarterly demand profiles, including maximum and minimum values, as well as inner and outer quartiles. This study simply relies on the median demand value for a weekday. These demand profiles are specific for each quarter, based on the only year for a complete set of EV Project charging data – 2012.

After determining time-specific total electricity demand across different BEV adoption scenarios, electrified-mile emissions can be estimated. Emissions estimation now becomes more complex, with unique electricity generating units (EGUs) entering as model components. Quarter-hour emissions rate tables were matched with interval electricity demands to determine daily and annual BEV emissions. Emissions rate tables for 6 pollutants (NO_x, SO_2, CH_4, N_2O, CO_eeq, PM_{10}, CO, and VOC) were developed at 15-minute intervals for all 4 quarters of 2012 on the ERCOT grid using emissions data from the eGRID database (EPA 2012b) and National Emissions Inventory (EPA 2001).[15] These data provides emissions rates for each of the 550 power generators on the ERCOT grid. Weighted average emissions rates for pollutant *p* are calculated for each fuel type *i* (coal, natural gas, oil, biomass) based on annual emissions (*A*) per power plant *j*, as follows:

$$w_{p,i} = \frac{x_{p,i,j} \times A_{i,j}}{\sum_j A_j}$$

where $x_{p,i,j}$ is the emissions rate for pollutant *p* of plant *j* combusting fuel type *i*. These emissions rates represent the marginal emissions of consuming one MWh of electricity by using a specific fuel type *i.* Total marginal grid emissions of a pollutant (*e*) therefore, is a function of fuel type shares (y_i) , and weighted average emissions rates, and interval BEV

[15] Emissions for NO_x, SO_2, CH_4, N_2O and CO_2eq were taken from actual plant emissions, as found in the eGRID data set, while PM_{10}, CO, and VOC are based only on grid-wide averages by fuel type, from the National Emissions Inventory Data set. These average rates were computed by dividing annual emissions from all plants of a given fuel type by the annual electricity generation. Therefore, these are unweighted estimates, compared to eGRID estimates, which are weighted by generation of each plant across a given fuel type.

energy demand (E_t). While weighted emissions rates were assumed constant, fuel type shares (y_i) change over time and by season. These changes are incorporated based on 15-minute ERCOT generation data, by fuel source, for every day in 2012. Simple averages of total production (per time interval [*t]*) are calculated for each quarter (*k)* to produce quarterly average fuel type shares ($y_{i,k,t}$). Therefore, quarterly emissions rates can be calculated as follows:

$$e_{p,k,t} = \sum_i y_{i,k,t} w_{p,i} E_t$$

This approach takes into account the fact that generation fuel type shares change as demand changes over time and season, for any marginal electricity usage. By "marginal" usage, it is assumed that the total BEV demand ($D_{i,j}$) does not affect the generation fuel type shares. In some cases, where BEV demand is very high, additional EGUs may be required to meet demand. At present, Texas's small PEV population has only a marginal effect on the grid, but if demand increases, perhaps even to 5% of total LDVs, this marginal demand assumption may no longer hold.

The final result for this approach is a lookup table of quarter-hour emissions rates, by season for 8 different pollutants. This is the table multiplied by total daily demand to determine daily emissions impacts of BEV charging. The result is in terms of aggregate emissions, but results could also be evaluated geographically by considering individual generator locations and proximity to urban areas.

It should be noted that the ERCOT generation mix data separates natural gas plants into two types – traditional and combined cycle. However, emissions rates from eGRID do not differentiate between the two types. ERCOT data indicates that roughly 50% of

Texas's natural-gas generators (unweighted by their individual power production levels) are combined cycle. Additionally, this study considers hydroelectric, solar, wind, and nuclear generators to be non-emitting, for all pollutants considered. This assumption is based on eGRID emissions rates, but it is important to understand that the life-cycle emissions of these power sources are not zero. Nuclear power is an especially controversial generating source, even though it produces zero emissions from direct generation. Risks of catastrophic meltdown and radiation exposures are a constant public concern, along with space and security demands of storing spent nuclear waste, which remains toxic for many years. Solar panels, too, require rare earth mining, wind turbines and hydroelectric power generators are also responsible for negative impacts on wildlife habitats (Tsoutsos et al. 2005, Rosenberg et al. 1997).

8.2 Life-Cycle Considerations

For a more complete evaluation of BEV versus CV emissions implications, some attention should be paid to life-cycle emissions, since BEVs generally require more energy (and thereby emissions) to construct, thanks mostly to battery assembly (Hawkins et al. 2012). This analysis uses embodied energy demands directly from Argonne National Laboratory's Greenhouse Gases, Regulated Emissions, and Energy Use in Transportation (GREET) model, which account for the upstream emissions and energy inputs required to produce all materials for typical light duty vehicles. These components include materials such as steel, plastic, iron, rubber and others, fluids (e.g., engine oil, power steering fluid, brake fluid), and batteries (used in CVs and more extensively in BEVs). GREET requires many assumptions regarding vehicle weight, materials, and inputs for upstream energy and emissions from power plants and transportation sources. The analysis here simply assumes all default estimates from GREET 2.1, as described originally by Wang (2001) and revised by Argonne National Laboratory (2013). This estimate of embodied energy across CVs and BEVs provides an additional dimension for a more holistic comparison between the two vehicle types for different electricity fuel mix scenarios.

CHAPTER 9 : EV EMISSIONS RESULTS

9.1 POWER PLANT EMISSIONS RATES

Average emission rates on the ERCOT grid are computed for 6 pollutant types with results shown in Table 9.1. Table 9.1's emission rates are based on eGRID and ERCOT data that vary by time-of-day and season. Other emissions rates provided later in this chapter (for PM, CO, and VOC) are ERCOT-wide averages, derived from the U.S.'s National Emissions Inventory (EPA 2001).

Table 9.1: Average ERCOT Emissions Rates (lb/MWh)

	NO_x	SO_2	CO_2	CH_4	N_2o	CO_2eq
Coal	4.04	19.2	6,503.2	284.7	422.3	6,537.5
Natural Gas	0.28	0.006	671.1	52.6	5.4	671.8
Other	0.11	1.8	683.3	28.1	41.2	641.6
Biomass	2.06E-4	1.41E-5	8.47E-5	0.276	0.037	0.004
Renewables, Nuclear	0	0	0	0	0	0

These rates are used to determine the emissions of electricity demand from BEV use, given a variable mix of these fuel types on the grid's feedstock. Figure 9.1 shows the anticipated shares, at 15-mintue intervals, for Q1 (winter-spring). A table of these values, for all quarters is shown in Appendix B.

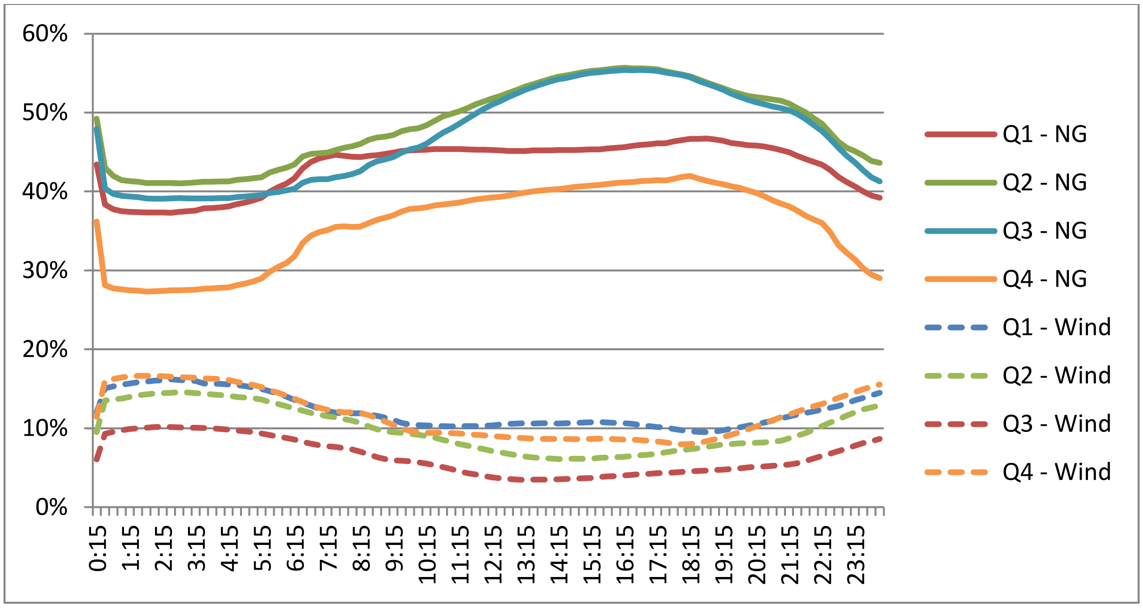

Figure 9.1: Average ERCOT Electricity Shares by Energy Source, Time of Day, and Season

BEV demand under several scenarios was considered, but only a few are explored here in detail. The model allows variation in shares of BEV versus PHEV and charging behavior, as well as fleet adoption across various years. Some of these cases are explored only briefly, and are held constant for subsequent analysis. For instance, an EV fleet of 100% BEV is considered from now on, to understand the unique emissions profiles of purely electric vehicles, and avoiding assumptions for share of electrified miles that each PHEV will deliver. One can use these results combined with PHEV and CV emissions rates to extend results to consider higher shares of PHEVs. Assuming only PEVs allows the analysis to focus on detailed methods and compare other scenarios such as charging profiles.

Comparing different charging profiles indicates little difference between charging scenarios, as shown in Table 9.2. This result is consistent with Thompson et al.'s (2011) findings of almost no difference between 4 different EV-charging profiles on the Texas grid.

Table 9.2: Average BEV Emissions by Charging Scenario on ERCOT grid (gram/mi)

	NO_x	SO_2	CH_4	N_2O	CO_2eq
Weekday	0.166	0.721	13.34	16.13	279.41
Weekend	0.165	0.722	13.33	16.16	279.48
Convenience	0.167	0.724	13.39	16.21	280.56
Off-Peak	0.166	0.732	13.02	16.33	276.95

Table 9.2's differences are rather small, and nearly negligible with the exception of perhaps CO_2eq. The difference in all PEVs charging when convenient (i.e., right when they arrive home) versus off-peak (for power generators, not necessarily roadway traffic) is about 6,730 tons of CO_2eq per year, or just a 1.3% decrease in grams per mile of a BEV's CO_2eq emissions. Since little difference exists by time of day, assuming average grid mixes (rather than a special, generator-specific dispatch model), the state's weekday charging emissions profile was assumed for the following results.

Emissions associated with different adoptions rates are shown in Figure 9.2, forecasted up to the year 2050. Adoption rates correspond to PEVs as shares of total passenger vehicles.

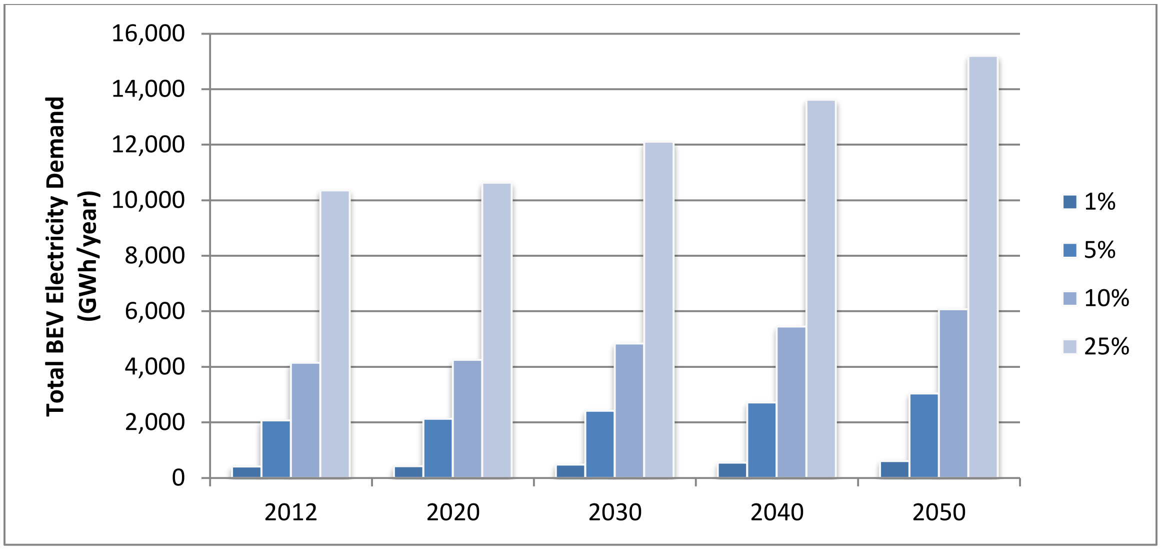

Figure 9.2: Total EV Power Demand in Texas Under Different New-Vehicle Purchase Shares

This result provides a sense of magnitude for energy demanded by BEVs under different vehicle-purchase scenarios, assuming average driving behaviors are maintained over time.

9.2 Conventional Vehicle Emissions

As an initial baseline for comparison, average CV emissions rates, estimated by Chester and Hovarth (2009) are considered here. One could use the MOVES emissions model for more precise estimates of CV emissions, but since EVs are only considered in the aggregate, such detail does not necessarily produce any greater accuracy overall. Table 9.3 presents compares average per-mile emissions for BEVs under different ERCOT fuel mixes, versus Chester and Horvath's (2009) CV emissions rates, estimated using the MOBILE6 model.

Table 9.3: CV vs. BEV Operating Emissions Rates (grams/mile)

	NO_x	SO_2	PM_{10}	CO	VOC	CH_4	N_2o	CO_2eq
Gas Sedan (C&H 2009)	0.85	0.021	0.110	11.0	0.310	--	--	370

Diesel Sedan (C&H 2009)	1.3	0.003	0.160	0.81	0.330	--	--	340
Gas LDT (C&H 2009)	1.4	0.034	0.100	16.0	0.640	--	--	620
Diesel LDT (C&H 2009)	1.3	0.005	0.150	0.71	0.470	--	--	570
EV: Avg. ERCOT Mix	0.17	0.72	0.014	0.15	0.002	13.34	16.13	280
EV: 100% Coal	0.47	2.23	0.036	0.43	0.005	33.14	49.15	761
EV: 100% NG	0.03	0.00	0.005	0.02	0.002	6.12	0.63	78
EV: 25% Increase in Renewables	0.12	0.54	0.011	0.11	0.002	10.01	12.10	210

Note: C&H stands for Chester and Horvath's (2009) emissions rate estimates.

Note that these results do not include cold start emissions, which are generally higher than operating emissions since emissions-control equipment (such as catalytic converters) have not reached optimal activation temperatures (Frey et al. 2002). Including cold start emissions would likely separate PEV and CV emissions further and should be considered in a more detailed emissions comparison.

These results highlight some major emissions profile differences between BEVs and various CV types. Interestingly, BEVs using the average mix (or with any instance of coal) will pollute SO_2 at much higher rates than conventional vehicles (as much as nearly 350 times for gasoline sedans vs. BEVs on the average ERCOT grid.) However, even when using 100% coal-sourced power, EVs are responsible for lower NO_x emissions than the average gasoline or diesel passenger car (per mile), less PM_{10}, less CO, and fewer VOCs, per average mile traveled. In terms of air quality, BEVs offer rather distinct advantages to the average CV, even in the worst case. Many U.S. regions are in non-attainment or near non-attainment with the national ozone standard (EPA 2013b), for example, and most are NO_x-limited (see, e.g., Carter 1994), meaning that another ton of NO_x in the airshed will mix with the relative excess of VOCs in the presence of sunlight and will raise ozone levels, everything lese constant. Thus, most regions would enjoy seeing overall airshed NO_x levels fall, to better avoid non-attainment. The major point of concern here, however, is that BEVs using 100% of Texas's average coal-fired power plants produce more than *twice* the GHGs (CO_2eq) of a typical gasoline passenger car, and 125% more GHGs than a diesel passenger car, per mile traveled. The GHG difference between a gasoline-powered SUV (or LDT) and coal-powered BEV passenger car is less pronounced, suggesting about a 20% increase for the BEV car, but still underscores the inherent inefficiency of using a BEV with a dirty fuel source. Fortunately today's average electric-power mix in Texas produces about 25% less CO_2eq per mile traveled on pure battery power than a typical gasoline-powered car.

9.3 Life-Cycle Analysis Comparison

Though the previous analysis provides some insight into the relative emissions profiles of vehicle use, consideration should be given to differences in emissions from vehicle production phases. This is done by including GREET's embodied emissions results alongside operations emissions, as shown in Figure 9.3.

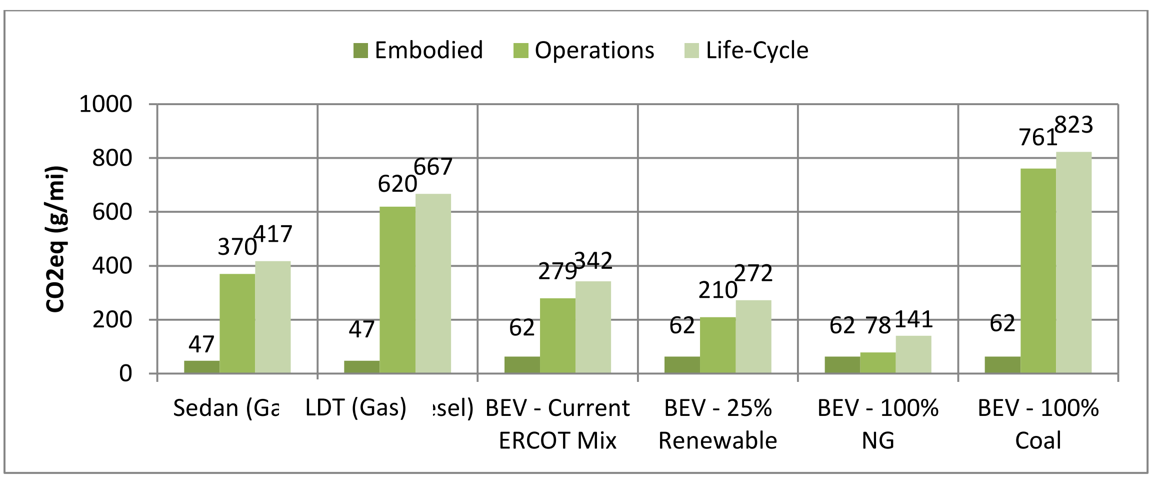

Figure 9.3: Life-Cycle CO_2eq Emissions of CVs vs. Pure-EV Scenarios

This analysis suggests that most life-cycle energy for conventional vehicles, and BEVs fueled by coal is from daily driving, rather than from production phases. Although BEV production might produce around 30% more CO_2eq than conventional vehicles, this phase is rather insignificant when compared to operations emissions. In fact, embodied energy comprised only about 11 and 7% of gasoline and diesel GHG emissions. A critical point to consider here is the life-cycle GHG emissions of conventional vehicles and BEVs using the current mix. These results suggest that such BEVs produce around 18% less GHG per mile than CVs, which could be reduced to 35% with increases in renewables or by nearly two-thirds with a 100% natural gas source.

A similar analysis can be performed for NO_x, which is more critical for meeting U.S. air quality standards (as discussed above), and has results shown in Figure 9.4.

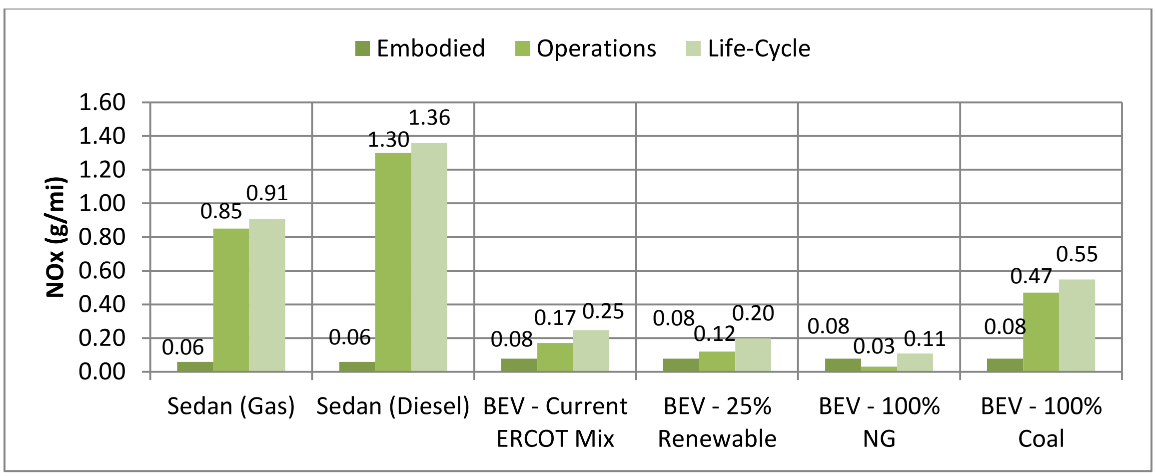

Figure 9.4: Life-Cycle NOx Emissions of CVs vs. BEV Scenarios

It is interesting to note that, for the 100% NG scenarios, the operations use phase produces fewer NO_x emissions than the embodied phase, which reverses the traditional ordering found for other vehicle types and fuel mix scenarios. CO_2eq emissions mimic this trend as well, with operations and embodied energy sources are nearly equal for a 100%

NG scenario, at least when assuming the relatively efficient generator types using on the ERCOT grid.

There is a case where BEVs, under any fuel mix scenario other than 100% renewables, perform worse than CVs – SO_2 emissions. Figure 9.5 shows that the average gasoline and diesel sedan produces very little on-road SO_2 compared to SO_2 from electricity generation. SO_2 causes both respiratory ailments (Frank et al. 1962) and contributes to acid rain (Park 1987).

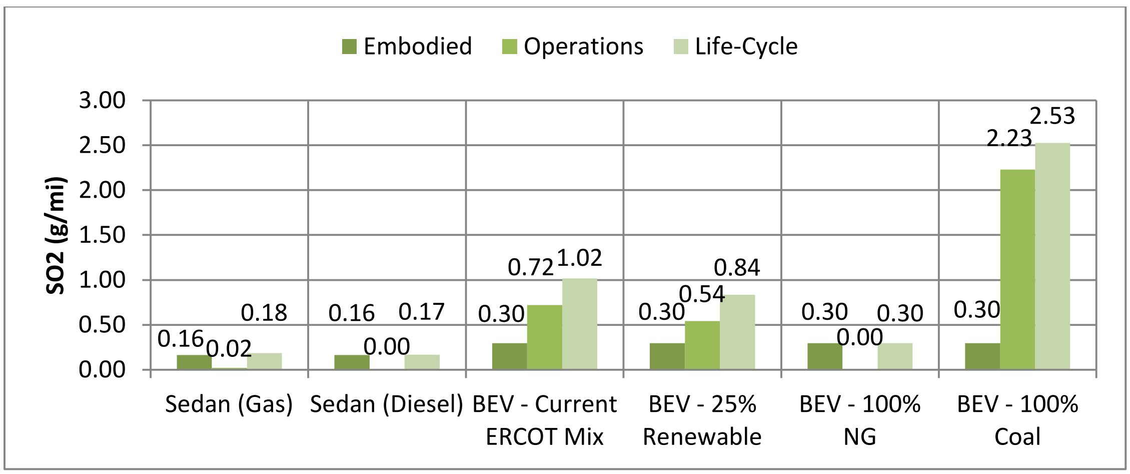

Figure 9.5: Life-Cycle SO_2 Emissions of CVs vs. BEV Scenarios

It should be noted that this life-cycle analysis does not necessarily consider the embodied energy associated with fuel production or power generation in the operations phase. That is, for gasoline, diesel, coal, natural gas, nuclear power, and other fuels, the only input is the amount of fuel consumed in the operations phase. Since the embodied phase of energy or fuel production is neglected, the magnitude of the operations phase is thereby underestimated for all vehicles. This may influence the magnitude of operations emissions differently across CVs and BEVs, but is unlikely to make a noticeable difference, since embodied-energy implications typically average 10 percent of the total energy use and will be overshadowed by the relative differences in operations. Exploring the embodied phase of operational energy leads to a recursive and increasingly complicated analysis focused on relatively negligible marginal emissions, so they are ignored in this case.

9.3 PEV Emissions Exposure

Though previous results suggest that PEV emissions rates for air quality pollutants are in most cases lower than those for CVs (with the exception SO_2), it is important to consider how emissions may shift over space and exposed populations, when shifting from CV use to EV use. Thompson et al. (2009, 2011) performed rather detailed spatial emissions analysis of EV emissions at point source locations, but that level of sophistication and expertise in air quality modeling is not replicated here. Rather, a general "exposure rate" is calculated for each ERCOT county, as the product of average power plant emissions rates[16] and population. Such a measure provides a sense of where the largest overall impacts from BEV usage are likely occurring, over the long term (since at any given time any number of the modeled plants may be operating). This measure is therefore a sense of the aggregate air quality risks posed by rising PEVs use.

The results indicate how urbanized area populations experience some of the greatest total exposures to power plant emissions, especially for CO, PM_{10}, and VOC, which is rather unsurprising given these areas' high population concentrations. However, there are some counties well away from Texas's major metropolitan areas of (Dallas-Fort Worth, Houston, San Antonio, and Austin) that show very high exposure rates for all power plant pollutants, especially for SO_2 and PM, as shown in Figure 9.6.

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[16] Each power plant's average emissions rates are weighted by that plant's annual electricity production.

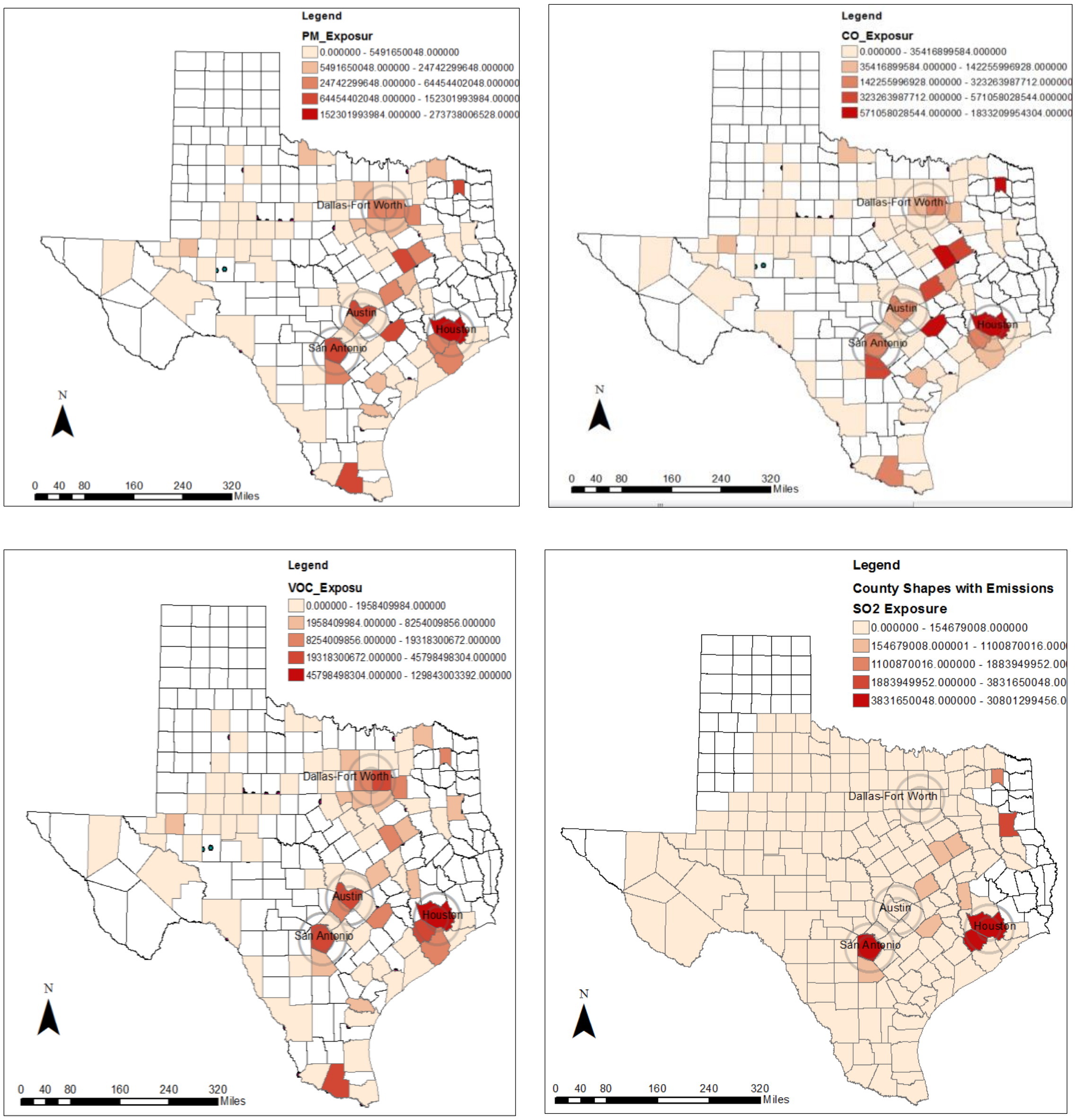

Figure 9.6: Total Emissions Exposure by County for PM, (top left) CO, (top right) VOC, (bottom left) and SO_2 (bottom right)

This result supports the idea that some rural areas may be subjected to higher emissions from EV adoption, use, and charging in urban areas, but the regions with more vehicles are more likely to carry the burden of exposure. In other words, enough power plants operate in Texas's major regions that EVs are not shifting all or even most of their associated emissions impacts to outlying areas, though there are certainly cases where the shifts may be disproportionate. Figure 9.6 highlights how EV charging emissions may often apply to less populated areas of Texas. Of course, CV users impose emissions externalities on occupants of the cars that follow them, and the pedestrians, cyclists, and school children that travel and play nearby. Without 100-percent clean transport technologies, one cannot avoid the issue of externalities and inequities in emissions impacts.

CHAPTER 10: CONCLUSIONS

This analysis confirms an already well-known fact: electricity produced from coal-burning power plants (both newer generation and older generation) is generally much more polluting than that produced by power plants relying on natural gas and renewables. While EVs powered exclusively by the average coal-fired power plant in Texas's ERCOT grid product around 3,200 times as much SO_2 (per mile-traveled), it is surprising to find their emissions rates of NO_x, CO, and VOCs are lower than those of CVs. Also somewhat surprising are the air quality and GHG savings associated with natural gas plants (with emissions rates based on current ERCOT averages for natural gas plants), and the relatively constant emissions rates (and feedstock mix) of Texas's power plants by time of day. Specifically, charging a BEV on the ERCOT grid with only coal plants emits over 14 times as much NO_x, 3,200 times as much SO_2, nearly 10 times as much CO_2 and CO_2eq, 2.5 times as much $PM_{10,}$ and VOCs, and nearly 80 times the N_2O compared to a grid with 100% natural gas plants. Of course, including a small share of biomass and renewables (including wind, hydroelectric, and solar power) will increase the savings more. This result indicates that coal plants, as already pointed out by Anair and Mahmassani (2012) are drastically more polluting than other fuel sources, as shown in Table 9.3

Overall, higher PEV shares in urban areas may help improve local air quality and help regions meet NAAQS for CO, N_2O, ozone, and PM (2.5 and 10), specifically. If, however, a region has any nearby coal plants that are sourcing BEVs and impacting regional air quality, BEVs may be creating much more of a problem for SO_2 concentrations than CVs would be. Since SO_2 emissions from coal plants (compared on a per-mile basis to CVs) are so relatively high, one should be cautious when using them to power any PEVs, especially in a place where coal emissions could be affecting large populations. All Texas counties are within NAAQS for SO_2, but several Midwest and East Coast counties are in nonattainment (EPA 2013), likely from higher concentrations of coal plants and heavy industry in these areas. Though SO_2 emissions are not necessarily a present concern in Texas, greater PEV demands being met with more coal plants (in populated areas) could be problematic. Since per-mile SO_2 emissions from BEVs powered by coal plants are so relatively high, adding an electrified mile to a system that depends on coal power would be equivalent to adding 3,200 CV miles, in terms of SO_2 emissions. This is an interesting result, because even at their relatively small shares, BEVs using coal-based electricity will have very disproportionate SO_2 emissions impacts. However, one should consider the societal costs of SO_2 (potentially from PEVs) versus other CV emissions (especially particulate matter) to best understand the extent of possible SO_2 emissions increases. Future work should explore these costs in more detail to better understand implications of trade-offs between SO_2 and other pollutants.

This study illustrates how a higher share of efficient natural gas and renewables (including nuclear) can significantly reduce BEV emissions, relative to CVs and BEVs using electricity largely provided by coal plants or inefficient natural gas plants. However, a focus on air emissions ignores some other environmental consequences of these energy production sources. Though producing little to no emissions, nuclear power is a well-known public safety and environmental risk, as well as a massive freshwater consumer (Gleick 1994). Natural gas, too, may be responsible for environmental issues related to water, as hydraulic fracturing techniques require a very large amount of freshwater, and could be degrading underground water stores (See, e.g., Osborn et al. 2011 and Entrekin et al. 2011) while releasing large amounts of global-warming methane (Howarth et al. 2011). Even wind turbines, solar panels, and hydroelectric power aren't immune from environmental damages – generators threaten certain migratory bird populations, solar panels require extensive land area that may disrupt animal habitats, and hydroelectric dams interrupt aquatic ecosystems. All this to say that there is no transportation energy solution that enjoys truly negligible costs, has zero environmental impact, and can move our world's growing population billions of miles per day. However, solutions like BEVs, with cleaner electricity sources, vehicles manufactured with less embodied emissions, and more efficient power sources and vehicles will help to reduce the impact of our mobility demands.

Appendix A

Table A1: Exogenous Inputs for Energy Models

Exogenous Inputs	Values	Notes
Vehicle Age	5 years	
Gasoline Cost	$3.50/gallon	U.S. average, summer 2013
Heavy Rail in Austin MSA?	1	(Yes=1)
MSA Size	3	(1 through 4)
Energy per Gallon Gas	132	MJ/US gallon
Cooling Degree Days (per year)	1350	Source: Tirumalachetty et al. 2013
Heating Degree Days (per year)	4489	Source: Tirumalachetty et al. 2013
U.S. Region	3	Source: Tirumalachetty et al. 2013
Natural Gas Price $/MMBTU	$10.90	Source: EIA
Electricity Price ($/kWh)	$0.09	Source: EIA

Table A2: Distribution of Household Types (Shown in Percentages)

		Workers											
		Low Income				Medium Income				High Income			
		0	1	2	3+	0	1	2	3+	0	1	2	3+
HH Size	1	0.10	10.50	0.00	0.00	1.85	10.06	0.00	0.00	0.11	0.87	0.00	0.00
	2	0.01	0.10	0.50	0.00	0.10	1.92	8.00	0.00	5.98	8.12	8.80	0.00
	3	1.78	1.49	1.49	0.09	1.49	1.62	1.62	0.52	1.49	1.64	1.64	0.53
	4	1.59	1.59	1.59	0.48	1.59	3.06	3.06	1.96	1.59	3.30	3.30	2.19

Table A3: Lifespan Assumptions

Component	Lifespan (Years)	Source(s)
Sidewalk	40	--
Street	20	--
SFH	50	Thormark (2002)
Duplex	75	Same as SFH
Tri-Fourplex	75	Same as SFH
Apartment	75	Gustavsson, et al. (2005)
Driveway	30	--
Office	75	Within ranges of Cole and Kernan (1996) and Ramesh et al. (2010)
Commercial	75	
Parking Garage	30	Guggemos & Horvath (2005)

Table A4: Embodied Energy Assumptions

Building Type	Embodied Energy (GJ/ft^2)	Source(s)
SFH	0.40	Hammond & Jones (2010), Adalberth (1997)
MFH	0.46	Hammond & Jones (2010)
Duplex	0.46	Hammond & Jones (2010)
Tri-Fourplex	0.46	Hammond & Jones (2010)
Apartment	0.46	Hammond & Jones (2010)
Office Building	0.45	Cole & Kernan (1996), Gustavsson and Joelsson (2010)
Commerical	0.45	
Surface Parking	0.06	Newton et al. (2000)
Parking Garage	0.12	Griffin et al. (2010)

Table A5: Total Neighborhood Operational Energy Estimates

Sector	Source	Operational Energy (GJs/Year)				
		R1 - WL	**R2 – AL**	**R3 – HP**	**R4 – RS**	**R5 – DT**
Transport	LDVs: Cars, Vans, SUVs, Trucks	234,720	150,321	180,667	194,603	37,984
Transport	Buses – Gasoline	2,751	1,369	1,155	2,214	395
Residential	Electricity + Natural Gas	249,259	158,125	196,209	269,627	216,209
Commercial-Office	Electricity + Natural Gas	136	6,372	56,928	28,434	2,266,877
Infrastructure	Lighting	1,967	945	471	551	6,153
Infrastructure	Water Use	2,615	1,779	2,655	4,154	2,963
Autos	VMT/cap	2,533	4,452	3,067	1,671	2,487
Autos	PMT	1,688	2,968	2,045	1,114	1,658
Buses	PMT	725,321	360,981	304,476	583,774	104,260
Buses	Avg. HH Trips	225	159	244	467	293
Buses	Avg. Trip Length (Miles)	4.2	2.9	1.6	1.6	0.5
Buses	Avg. Passenger Miles	944	470	398	760	136

Table A6: Total Neighborhood Embodied Energy Estimates

Sector	Source	Embodied Energy (GJs/Year)				
		R1 – WL	**R2 – AL**	**R3 – HP**	**R4 – RS**	**R5 – DT**
Transport	Cars	0	0	367	0	297
Transport	Parking Garages	2	1	2,149	9,024	193
Transport	Surface Parking	264	1,065	567	320	2,113
Infrastructure	Sidewalk	42,137	36,737	36,458	20,566	70,491
Infrastructure	Streets and Roads	1,679	838	1,193	2,030	3,465
Infrastructure	Water Pipes	676	396	847	227	4,626
Infrastructure	Wastewater Pipes	67,985	32,703	23,426	2,019	1,637
Buildings	Single-Family Home	205	0	951	393	31
Buildings	Duplex	19	0	215	0	53
Buildings	Three- and Four-Plex	3,859.6	3,441.2	6,534.1	13,978.1	24,176.9
Buildings	Apartments	3	0	1,738	42	132,890
Buildings	Office	2	5,334	17,064	21,992	2,665
Buildings	Commercial	0	0	367	0	297

The following images show a 10-mile radius of zones around city centers in modeled regions. Averages for one-mile radius bands were calculated based on SLD zone centroids.

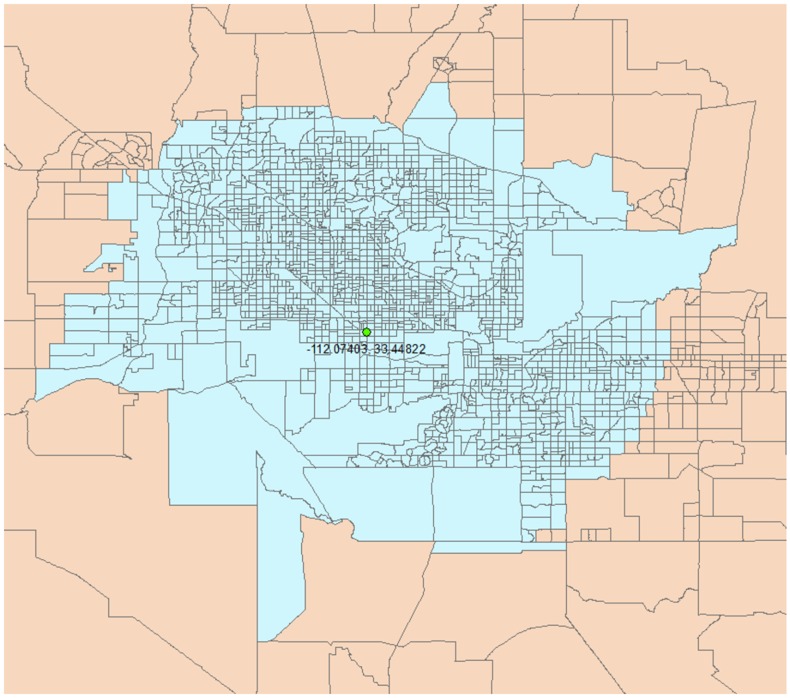

Figure A1: Phoenix SLD Zones Included in Density and Accessibility Calculations

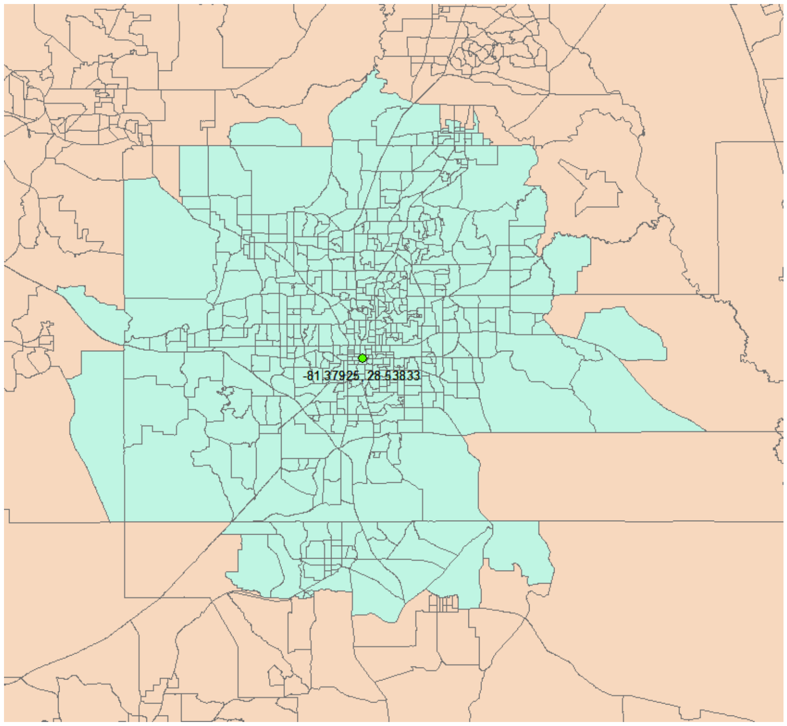

Figure A2: Orlando SLD Zones Included in Density and Accessibility Calculations

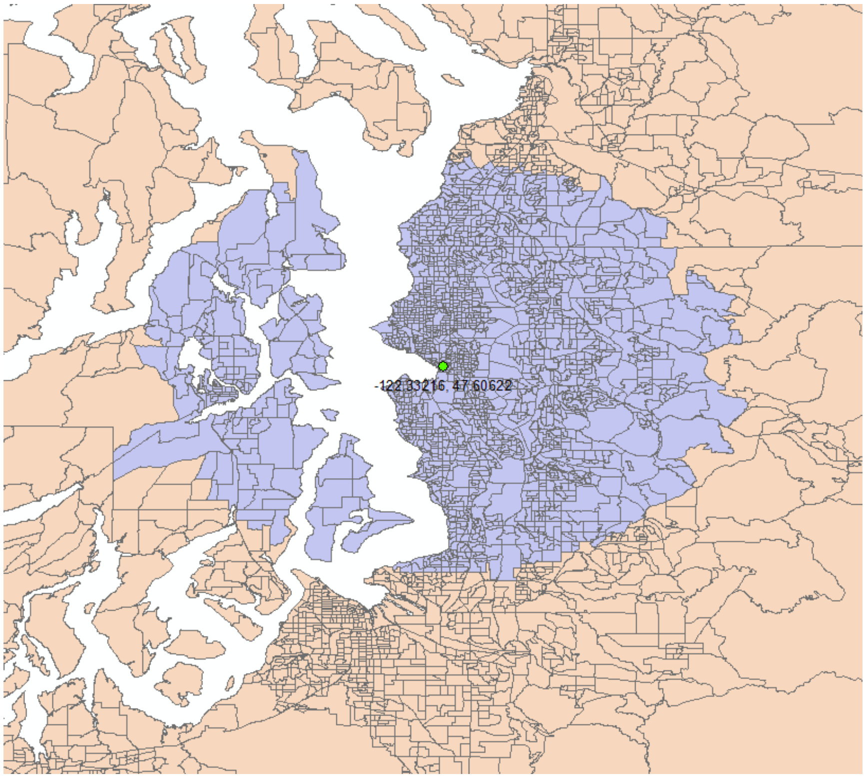

Figure A3: Seattle SLD Zones Included in Density and Accessibility Calculations

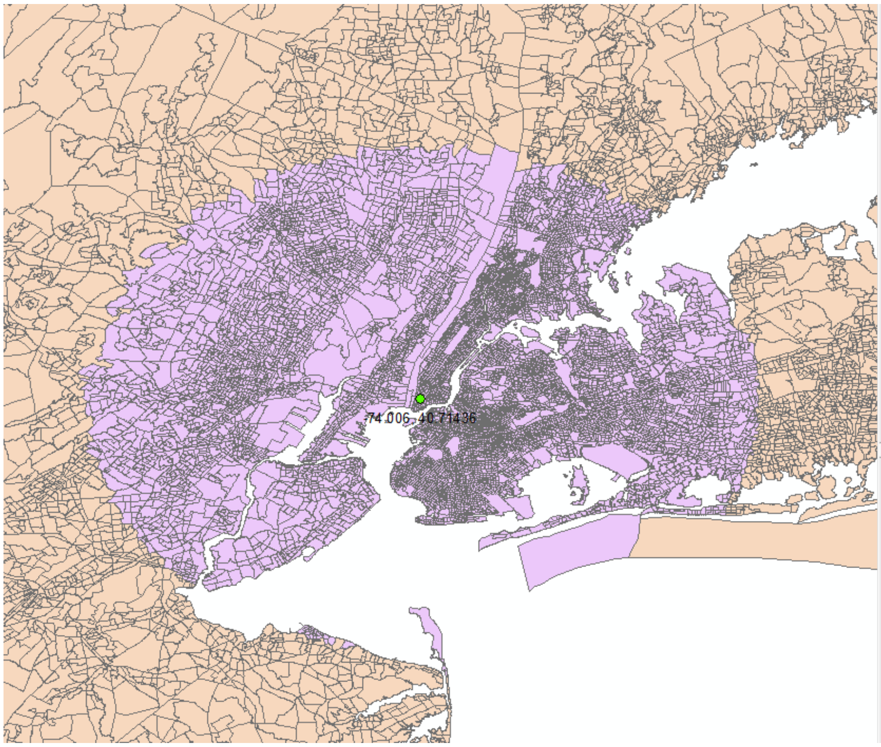

Figure A4: New York SLD Zones Include in Density and Accessibility Calculations

All city center calculations are from EPA's Smart Location Database (SLD). Latitude and longitude are calculated for each SLD zone centroid, and city centers are designated as follows:

Table A7: City Center Locations and SLD Zones

City	General Location	Latitude	Longitude
Austin, TX	6th St. and Congress Ave.	30.2680	-97.7428
Seattle, WA	5th St. and Madison St.	47.6062	-122.33216
Phoenix, AZ	Central Ave. and Washington St.	33.4482	-112.07403
New York, NY	Reade St. and Broadway	40.7144	-74.00600
Orlando, FL	South St. and Orange Ave.	28.5383	-81.37925

Table 8 reports resident and worker populations by neighborhood type, along with total resident and worker populations, for all model cities.

Table A8: Model City Neighborhood Type, Population and Employment Distribution

		Orlando	Phoenix	Austin	Seattle	New York
Residential Neighborhoods (count)	1R – WL	51	42	48	3	0
	2R – AM	222	138	49	85	0
	3R – HP	20	53	70	90	0
	4R – RS	4	68	31	62	308
	5R – DT	4	5	3	0	0
	Total Area Occupied (mi^2)	301	306	201	240	308
Commercial Neighborhoods (Count)	1C – RS	142	42	97	30	16
	2C – HP	150	252	47	170	188
	3C – DT	3	13	5	10	56
	Total Area Occupied (mi^2)	295	307	149	210	260
Resident Population	1R – WL	49,035	40,382	46,151	2,884	0
	2R – AM	1,364,878	848,438	301,257	522,589	0
	3R – HP	114,260	302,789	399,910	514,170	0
	4R – RS	68,997	1,172,935	534,720	1,069,440	5,312,704
	5R – DT	19,432	24,290	14,574	0	0
	Total Resident Population	1,616,601 1,616,601	2,388,833	1,296,611	2,109,083	5,312,704
Employment	1C – RS	284,301	84,089	194,206	60,064	32,034
	2C – HP	347,532	583,854	108,893	393,870	435,574
	3C – DT	229,743	995,551	382,904	765,808	4,288,527
	Total Jobs	861,576	1,663,494	686,003	1,219,742	4,756,135
Resident-Worker Ratio		1.88	1.44	1.89	1.73	1.12

Appendix B

Table B1: EV Charging Profile Summary for Q1, 2012

	DFW	Houston	All U.S. Locations
	Q1, 2012		
Number of EV Project Vehicles	58	46	3304
Number of Charging Units	124	75	4289
Number of Charging Events	5336	3877	227314
Electricity Consumed (AC MWh)	27.27	25.53	1858.55
% Time a vehicle is connected to charging unit	0.24	0.29	0.29
% Time vehicle is drawing power	0.04	0.05	0.06
Average over Quarter			
Charge Events per Vehicle	92.00	84.28	68.80
AC MWh consumed per vehicle	0.47	0.56	0.56
Average per Day			
Charge Events per Vehicle	1.02	0.94	0.76
AC kWh consumed per vehicle	5.22	6.17	6.25

Table B2: EV Charging Profile Summary for Q2, 2012

	DFW	Houston	All U.S. Locations
	Q2, 2012		
Number of EV Project Vehicles	65	45	3325
Number of Charging Units	172	92	4821
Number of Charging Events	7239	3967	250953
Electricity Consumed (AC MWh)	41.56	26.44	2094.49
% Time a vehicle is connected to charging unit	0.23	0.27	0.28
% Time vehicle is drawing power form charging unit	0.04	0.05	0.06
Average over Quarter			
Charge Events per Vehicle	111.37	88.16	75.47
AC MWh consumed per vehicle	0.64	0.59	0.63
Average per Day			
Charge Events per Vehicle	1.22	0.97	0.83
AC kWh consumed per vehicle	7.03	6.46	6.92

Table B3: EV Charging Profile Summary for Q3, 2012

	DFW	Houston	All U.S. Locations
	Q3, 2012		
Number of EV Project Vehicles	109	59	4009
Number of Charging Units	225	98	5877
Number of Charging Events	8692	4860	289364
Electricity Consumed (AC MWh)	55.91	32.82	2322.6
% Time a vehicle is connected to charging unit	0.24	0.29	0.27
% Time vehicle is drawing power form charging unit	0.05	0.06	0.06
Average over Quarter			
Charge Events per Vehicle	79.74	82.37	72.18
AC MWh consumed per vehicle	0.51	0.56	0.58
Average per Day			
Charge Events per Vehicle	0.87	0.90	0.78
AC kWh consumed per vehicle	5.58	6.05	6.30

Table B4: EV Charging Profile Summary for Q4, 2012

	DFW	Houston	All U.S. Locations
Number of EV Project Vehicles	125	60	4783
Number of Charging Units	270	115	6939
Number of Charging Events	13970	5722	388606
Electricity Consumed (AC MWh)	84.24	36.83	3212.3
% Time a vehicle is connected to charging unit	0.28	0.27	0.31
% Time vehicle is drawing power form charging unit	0.05	0.05	0.06
Average over Quarter			
Charge Events per Vehicle	111.76	95.37	81.25
AC MWh consumed per vehicle	0.67	0.61	0.67
Average per Day			
Charge Events per Vehicle	1.21	1.04	0.88
AC kWh consumed per vehicle	7.33	6.67	7.30

Table B5: Normalized Charging Profile, U.S. Median, by Weekday (WD) and Weekend (WE)

	WD Q2 2012	WE Q2 2012	WD Q3 2012	WE Q3 2012	WD Q4 2012	WE Q4 2012	WD Q1 2013	WE Q1 2013	WD Q2 2013	WE Q2 2013
	Median									
0:00	0.0109	0.0141	0.0138	0.0121	0.0122	0.0141	0.0131	0.0128	0.0138	0.0128
0:15	0.0102	0.0142	0.0136	0.0106	0.0107	0.0142	0.0119	0.0110	0.0126	0.0127
0:30	0.0095	0.0146	0.0120	0.0109	0.0094	0.0146	0.0110	0.0095	0.0115	0.0118
0:45	0.0081	0.0137	0.0114	0.0102	0.0085	0.0137	0.0097	0.0093	0.0101	0.0100
1:00	0.0069	0.0123	0.0100	0.0089	0.0073	0.0123	0.0088	0.0081	0.0092	0.0089
1:15	0.0065	0.0107	0.0091	0.0088	0.0068	0.0107	0.0079	0.0072	0.0081	0.0080
1:30	0.0061	0.0098	0.0088	0.0077	0.0062	0.0098	0.0070	0.0064	0.0074	0.0072
1:45	0.0057	0.0088	0.0079	0.0072	0.0054	0.0088	0.0063	0.0058	0.0064	0.0067
2:00	0.0069	0.0100	0.0077	0.0067	0.0048	0.0100	0.0055	0.0054	0.0058	0.0060
2:15	0.0053	0.0086	0.0069	0.0057	0.0046	0.0086	0.0050	0.0050	0.0051	0.0050
2:30	0.0053	0.0083	0.0061	0.0046	0.0040	0.0083	0.0046	0.0043	0.0049	0.0051
2:45	0.0052	0.0075	0.0058	0.0048	0.0035	0.0075	0.0043	0.0038	0.0042	0.0047
3:00	0.0045	0.0067	0.0055	0.0045	0.0034	0.0067	0.0039	0.0039	0.0037	0.0041
3:15	0.0039	0.0066	0.0056	0.0045	0.0033	0.0066	0.0036	0.0039	0.0033	0.0034
3:30	0.0037	0.0057	0.0051	0.0041	0.0032	0.0057	0.0033	0.0032	0.0031	0.0033
3:45	0.0034	0.0047	0.0048	0.0037	0.0031	0.0047	0.0028	0.0025	0.0028	0.0039
4:00	0.0026	0.0043	0.0046	0.0038	0.0026	0.0043	0.0027	0.0023	0.0025	0.0039
4:15	0.0028	0.0045	0.0045	0.0034	0.0023	0.0045	0.0026	0.0017	0.0024	0.0035
4:30	0.0023	0.0037	0.0037	0.0032	0.0014	0.0037	0.0021	0.0016	0.0019	0.0035
4:45	0.0020	0.0030	0.0024	0.0024	0.0009	0.0030	0.0018	0.0016	0.0016	0.0030
5:00	0.0018	0.0024	0.0021	0.0018	0.0009	0.0024	0.0016	0.0014	0.0015	0.0026
5:15	0.0018	0.0022	0.0021	0.0018	0.0009	0.0022	0.0016	0.0012	0.0015	0.0025
5:30	0.0018	0.0023	0.0020	0.0024	0.0012	0.0023	0.0015	0.0011	0.0015	0.0023
5:45	0.0018	0.0022	0.0019	0.0022	0.0015	0.0022	0.0015	0.0015	0.0014	0.0020
6:00	0.0018	0.0021	0.0017	0.0023	0.0015	0.0021	0.0011	0.0017	0.0012	0.0020
6:15	0.0018	0.0021	0.0019	0.0023	0.0015	0.0021	0.0014	0.0015	0.0014	0.0019
6:30	0.0015	0.0020	0.0019	0.0031	0.0018	0.0020	0.0017	0.0015	0.0017	0.0017
6:45	0.0019	0.0009	0.0024	0.0023	0.0024	0.0009	0.0021	0.0012	0.0019	0.0017
7:00	0.0028	0.0020	0.0028	0.0026	0.0029	0.0020	0.0029	0.0014	0.0024	0.0019
7:15	0.0035	0.0021	0.0031	0.0033	0.0034	0.0021	0.0033	0.0017	0.0026	0.0024

7:30	0.0036	0.0021	0.0033	0.0027	0.0035	0.0021	0.0034	0.0021	0.0029	0.0026
7:45	0.0037	0.0021	0.0043	0.0028	0.0045	0.0021	0.0041	0.0021	0.0036	0.0023
8:00	0.0043	0.0016	0.0051	0.0027	0.0052	0.0016	0.0053	0.0024	0.0046	0.0028
8:15	0.0045	0.0022	0.0057	0.0025	0.0060	0.0022	0.0056	0.0025	0.0047	0.0029
8:30	0.0043	0.0021	0.0052	0.0023	0.0061	0.0021	0.0059	0.0028	0.0045	0.0030
8:45	0.0035	0.0020	0.0046	0.0027	0.0058	0.0020	0.0055	0.0031	0.0046	0.0033
9:00	0.0034	0.0021	0.0043	0.0026	0.0072	0.0021	0.0062	0.0030	0.0054	0.0035
9:15	0.0035	0.0020	0.0043	0.0023	0.0071	0.0020	0.0068	0.0035	0.0056	0.0043
9:30	0.0035	0.0022	0.0040	0.0038	0.0065	0.0022	0.0070	0.0044	0.0054	0.0049
9:45	0.0041	0.0027	0.0039	0.0047	0.0065	0.0027	0.0067	0.0043	0.0051	0.0048
10:00	0.0040	0.0027	0.0039	0.0053	0.0060	0.0027	0.0062	0.0047	0.0049	0.0049
10:15	0.0043	0.0046	0.0041	0.0055	0.0057	0.0046	0.0062	0.0057	0.0049	0.0057
10:30	0.0048	0.0047	0.0042	0.0054	0.0053	0.0047	0.0056	0.0062	0.0048	0.0068
10:45	0.0044	0.0054	0.0045	0.0058	0.0056	0.0054	0.0056	0.0063	0.0050	0.0072
11:00	0.0048	0.0069	0.0046	0.0071	0.0053	0.0069	0.0054	0.0073	0.0048	0.0074
11:15	0.0051	0.0074	0.0044	0.0075	0.0046	0.0074	0.0054	0.0073	0.0049	0.0084
11:30	0.0053	0.0072	0.0047	0.0074	0.0050	0.0072	0.0054	0.0078	0.0050	0.0092
11:45	0.0056	0.0073	0.0050	0.0072	0.0052	0.0073	0.0053	0.0093	0.0052	0.0094
12:00	0.0065	0.0090	0.0054	0.0072	0.0053	0.0090	0.0056	0.0100	0.0059	0.0100
12:15	0.0067	0.0109	0.0065	0.0087	0.0062	0.0109	0.0063	0.0100	0.0064	0.0105
12:30	0.0074	0.0124	0.0072	0.0102	0.0066	0.0124	0.0068	0.0114	0.0068	0.0117
12:45	0.0080	0.0131	0.0080	0.0121	0.0066	0.0131	0.0068	0.0124	0.0070	0.0126
13:00	0.0088	0.0130	0.0079	0.0130	0.0068	0.0130	0.0076	0.0140	0.0071	0.0133
13:15	0.0090	0.0142	0.0071	0.0147	0.0077	0.0142	0.0081	0.0150	0.0075	0.0137
13:30	0.0097	0.0143	0.0076	0.0158	0.0081	0.0143	0.0080	0.0155	0.0075	0.0141
13:45	0.0097	0.0126	0.0075	0.0142	0.0085	0.0126	0.0082	0.0157	0.0072	0.0140
14:00	0.0103	0.0139	0.0078	0.0131	0.0089	0.0139	0.0081	0.0155	0.0073	0.0150
14:15	0.0101	0.0151	0.0084	0.0134	0.0086	0.0151	0.0079	0.0161	0.0074	0.0154
14:30	0.0110	0.0158	0.0084	0.0141	0.0092	0.0158	0.0076	0.0159	0.0073	0.0154
14:45	0.0114	0.0144	0.0080	0.0146	0.0087	0.0144	0.0076	0.0163	0.0075	0.0152
15:00	0.0119	0.0137	0.0092	0.0143	0.0091	0.0137	0.0076	0.0176	0.0079	0.0153
15:15	0.0127	0.0155	0.0100	0.0142	0.0091	0.0155	0.0081	0.0174	0.0084	0.0163
15:30	0.0139	0.0179	0.0108	0.0145	0.0099	0.0179	0.0085	0.0182	0.0090	0.0165
15:45	0.0155	0.0166	0.0115	0.0141	0.0101	0.0166	0.0090	0.0183	0.0094	0.0165
16:00	0.0158	0.0164	0.0117	0.0161	0.0104	0.0164	0.0091	0.0188	0.0095	0.0168
16:15	0.0172	0.0155	0.0119	0.0156	0.0117	0.0155	0.0094	0.0187	0.0105	0.0167
16:30	0.0177	0.0168	0.0134	0.0170	0.0137	0.0168	0.0112	0.0180	0.0123	0.0174
16:45	0.0188	0.0166	0.0146	0.0172	0.0150	0.0166	0.0126	0.0179	0.0136	0.0167
17:00	0.0182	0.0170	0.0153	0.0165	0.0157	0.0170	0.0145	0.0188	0.0144	0.0167

17:15	0.0195	0.0169	0.0164	0.0169	0.0171	0.0169	0.0165	0.0184	0.0165	0.0180
17:30	0.0207	0.0166	0.0190	0.0156	0.0191	0.0166	0.0181	0.0182	0.0185	0.0181
17:45	0.0219	0.0170	0.0196	0.0174	0.0205	0.0170	0.0197	0.0183	0.0204	0.0167
18:00	0.0216	0.0160	0.0216	0.0179	0.0206	0.0160	0.0215	0.0182	0.0221	0.0165
18:15	0.0232	0.0171	0.0239	0.0191	0.0224	0.0171	0.0230	0.0196	0.0235	0.0163
18:30	0.0232	0.0163	0.0250	0.0177	0.0253	0.0163	0.0253	0.0198	0.0251	0.0163
18:45	0.0237	0.0165	0.0252	0.0177	0.0257	0.0165	0.0269	0.0190	0.0254	0.0162
19:00	0.0249	0.0155	0.0256	0.0194	0.0263	0.0155	0.0271	0.0186	0.0261	0.0163
19:15	0.0246	0.0144	0.0255	0.0193	0.0262	0.0144	0.0277	0.0192	0.0265	0.0162
19:30	0.0231	0.0165	0.0247	0.0197	0.0260	0.0165	0.0274	0.0199	0.0266	0.0167
19:45	0.0227	0.0170	0.0232	0.0199	0.0260	0.0170	0.0270	0.0200	0.0260	0.0167
20:00	0.0219	0.0184	0.0226	0.0205	0.0250	0.0184	0.0270	0.0192	0.0260	0.0166
20:15	0.0221	0.0184	0.0219	0.0215	0.0245	0.0184	0.0265	0.0184	0.0256	0.0170
20:30	0.0210	0.0176	0.0214	0.0207	0.0243	0.0176	0.0254	0.0173	0.0255	0.0168
20:45	0.0213	0.0176	0.0203	0.0204	0.0243	0.0176	0.0243	0.0175	0.0253	0.0171
21:00	0.0205	0.0170	0.0203	0.0201	0.0238	0.0170	0.0236	0.0172	0.0249	0.0178
21:15	0.0211	0.0156	0.0195	0.0191	0.0227	0.0156	0.0229	0.0155	0.0245	0.0173
21:30	0.0199	0.0157	0.0194	0.0173	0.0221	0.0157	0.0222	0.0148	0.0237	0.0172
21:45	0.0200	0.0155	0.0191	0.0171	0.0216	0.0155	0.0209	0.0152	0.0227	0.0169
22:00	0.0191	0.0160	0.0189	0.0146	0.0211	0.0160	0.0197	0.0160	0.0217	0.0165
22:15	0.0174	0.0160	0.0187	0.0149	0.0195	0.0160	0.0186	0.0152	0.0202	0.0173
22:30	0.0162	0.0153	0.0181	0.0154	0.0187	0.0153	0.0172	0.0147	0.0190	0.0171
22:45	0.0158	0.0144	0.0178	0.0154	0.0177	0.0144	0.0159	0.0144	0.0178	0.0166
23:00	0.0159	0.0151	0.0180	0.0158	0.0172	0.0151	0.0158	0.0149	0.0173	0.0167
23:15	0.0146	0.0145	0.0162	0.0151	0.0158	0.0145	0.0152	0.0143	0.0165	0.0149
23:30	0.0129	0.0150	0.0144	0.0149	0.0144	0.0150	0.0143	0.0132	0.0155	0.0146
23:45	0.0120	0.0142	0.0144	0.0141	0.0134	0.0142	0.0133	0.0131	0.0140	0.0137
Sum	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000

Table B: EV Demand Scenarios

Year	Adoption Scenario	# Vehicles	Total Annual Demand (GWh)	Total Demand (Wh/Day)	Share BEV
2012	1%	155,820	406.6	1113953674	0
2012	1%	155,820	408.5	1119207632	0.25
2012	1%	155,820	410.4	1124461591	0.5
2012	1%	155,820	412.3	1129715549	0.75
2012	1%	155,820	414.3	1134969507	1
2012	5%	779,099	2033.0	5569761221	0
2012	5%	779,099	2042.6	5596030979	0.25
2012	5%	779,099	2052.1	5622300736	0.5
2012	5%	779,099	2061.7	5648570494	0.75
2012	5%	779,099	2071.3	5674840251	1
2012	10%	1,558,197	4065.9	11139515294	0
2012	10%	1,558,197	4085.1	11192054775	0.25
2012	10%	1,558,197	4104.3	11244594256	0.5
2012	10%	1,558,197	4123.5	11297133737	0.75
2012	10%	1,558,197	4142.6	11349673218	1
2012	25%	3,895,494	10164.8	27848798957	0
2012	25%	3,895,494	10212.8	27980147711	0.25
2012	25%	3,895,494	10260.7	28111496465	0.5
2012	25%	3,895,494	10308.6	28242845218	0.75
2012	25%	3,895,494	10356.6	28374193972	1
2020	1%	159,936	417.3	1143378865	0
2020	1%	159,936	419.3	1148771607	0.25
2020	1%	159,936	421.3	1154164350	0.5
2020	1%	159,936	423.2	1159557092	0.75
2020	1%	159,936	425.2	1164949834	1
2020	5%	799,682	2086.7	5716908625	0
2020	5%	799,682	2096.5	5743872403	0.25
2020	5%	799,682	2106.4	5770836180	0.5
2020	5%	799,682	2116.2	5797799958	0.75
2020	5%	799,682	2126.0	5824763736	1
2020	10%	1,599,364	4173.3	11433817250	0
2020	10%	1,599,364	4193.0	11487744806	0.25
2020	10%	1,599,364	4212.7	11541672361	0.5

2020	10%	1,599,364	4232.4	11595599916	0.75
2020	10%	1,599,364	4252.1	11649527471	1
2020	25%	3,998,409	10433.4	28584535977	0
2020	25%	3,998,409	10482.6	28719354831	0.25
2020	25%	3,998,409	10531.8	28854173686	0.5
2020	25%	3,998,409	10581.0	28988992540	0.75
2020	25%	3,998,409	10630.2	29123811395	1
2030	1%	182,137	475.3	1302093315	0
2030	1%	182,137	477.5	1308234633	0.25
2030	1%	182,137	479.7	1314375951	0.5
2030	1%	182,137	482.0	1320517269	0.75
2030	1%	182,137	484.2	1326658587	1
2030	5%	910,687	2376.3	6510480873	0
2030	5%	910,687	2387.5	6541187531	0.25
2030	5%	910,687	2398.7	6571894189	0.5
2030	5%	910,687	2409.9	6602600847	0.75
2030	5%	910,687	2421.2	6633307505	1
2030	10%	1,821,374	4752.7	13020961745	0
2030	10%	1,821,374	4775.1	13082375061	0.25
2030	10%	1,821,374	4797.5	13143788377	0.5
2030	10%	1,821,374	4819.9	13205201694	0.75
2030	10%	1,821,374	4842.3	13266615010	1
2030	25%	4,553,436	11881.6	32552411512	0
2030	25%	4,553,436	11937.7	32705944836	0.25
2030	25%	4,553,436	11993.7	32859478160	0.5
2030	25%	4,553,436	12049.7	33013011484	0.75
2030	25%	4,553,436	12105.8	33166544809	1
2040	1%	204,843	534.5	1464417998	0
2040	1%	204,843	537.0	1471324920	0.25
2040	1%	204,843	539.6	1478231842	0.5
2040	1%	204,843	542.1	1485138764	0.75
2040	1%	204,843	544.6	1492045686	1
2040	5%	1,024,216	2672.6	7322097139	0
2040	5%	1,024,216	2685.2	7356631782	0.25
2040	5%	1,024,216	2697.8	7391166425	0.5
2040	5%	1,024,216	2710.4	7425701068	0.75
2040	5%	1,024,216	2723.0	7460235712	1
2040	10%	2,048,433	5345.1	14644201427	0

2040	10%	2,048,433	5370.3	14713270747	0.25
2040	10%	2,048,433	5395.6	14782340067	0.5
2040	10%	2,048,433	5420.8	14851409387	0.75
2040	10%	2,048,433	5446.0	14920478707	1
2040	25%	5,121,082	13362.8	36610499994	0
2040	25%	5,121,082	13425.9	36783173277	0.25
2040	25%	5,121,082	13488.9	36955846560	0.5
2040	25%	5,121,082	13551.9	37128519843	0.75
2040	25%	5,121,082	13614.9	37301193126	1
2050	1%	228,613	596.5	1634349193	0
2050	1%	228,613	599.4	1642057595	0.25
2050	1%	228,613	602.2	1649765997	0.5
2050	1%	228,613	605.0	1657474398	0.75
2050	1%	228,613	607.8	1665182800	1
2050	5%	1,143,066	2982.7	8171753115	0
2050	5%	1,143,066	2996.8	8210295157	0.25
2050	5%	1,143,066	3010.8	8248837200	0.5
2050	5%	1,143,066	3024.9	8287379242	0.75
2050	5%	1,143,066	3039.0	8325921284	1
2050	10%	2,286,131	5965.4	16343499081	0
2050	10%	2,286,131	5993.5	16420583132	0.25
2050	10%	2,286,131	6021.6	16497667183	0.5
2050	10%	2,286,131	6049.8	16574751234	0.75
2050	10%	2,286,131	6077.9	16651835284	1
2050	25%	5,715,328	14913.4	40858751277	0
2050	25%	5,715,328	14983.8	41051461421	0.25
2050	25%	5,715,328	15054.1	41244171565	0.5
2050	25%	5,715,328	15124.5	41436881709	0.75
2050	25%	5,715,328	15194.8	41629591853	1

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Vita

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